



University Advancing in Manufacturing Sustainability Measurements: A Machine Learning Framework for Decoupling Industrial Growth from Carbon Emissions Across 123 Countries

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Abstract

This study examines the relationship between manufacturing value added (MVA) and carbon dioxide (CO₂) emissions across national contexts by adapting a dual-methodology approach. This paper combines traditional linear regression with random forest machine learning algorithms. As global manufacturing continues to grow, understanding both absolute emissions and carbon intensity (emissions per unit of economic output) becomes crucial for sustainable development. We address two key questions: How do CO₂ emissions and carbon intensity respond to changes in manufacturing value added? What are the future emission patterns based on manufacturing trends? This study employs comprehensive datasets from 123 countries spanning 2000-2022, analyzing both absolute emissions and carbon efficiency metrics. The study reveals that while manufacturing growth drives absolute emissions (elasticity: 0.59), carbon intensity shows declining trends in developed countries. This is indicating potential for decoupling economic growth from environmental impact. These findings support evidence-based policymaking for emission reduction strategies and provide quantitative foundations for balancing economic growth with environmental sustainability.

Keywords: *Manufacturing Value Added - Carbon Dioxide Emissions - Random Forest - Predictive Modeling – Machine Learning*

1. Introduction

Random forest is a machine learning algorithm that builds a collective decision tree to improve. The sole purpose of machine learning in general, not just Random Forest, is to give a prediction that is characterized by accuracy and handles large-scale data. As the name suggests, it's like a forest with trees, but each tree in the forest is trained on a random subset of the data and features. Then comes the second phase, which is predictions that are made by aggregating the outputs of all trees through majority voting for classification or averaging for regression tasks (Schonlau & Zou, 2020; Liu et al., 2012; Murphy & Moore, 2019). Furthermore, this algorithm offers strong capabilities in both the classification and the regression calculation of a given problem. With its applications that range from credit risk assessment to medical diagnostics and bioinformatics (Schonlau & Zou, 2020; Denisko & Hoffman, 2018; Murphy & Moore, 2019). Specifically, Random Forest is valued for its simplicity, robustness, and ability to handle high-dimensional data without extensive parameter tuning amongst many models of machine learning (Liu et al., 2012; Denisko & Hoffman, 2018; Segal, 2004). Recent research has focused on improving random forest performance by increasing the diversity and accuracy of individual trees. (Karabadjji et al., 2023; Savargiv et al., 2021; Sun et al., 2023). In addition to that, the enhanced versions of random forests have demonstrated superior accuracy and stability compared to traditional methods of predictions in the field of research. Especially when this algorithm addresses issues like correlation and data variability (Karabadjji et al., 2023; Savargiv et al., 2021; Sun et al., 2023). Overall, random forest remains a cornerstone of machine learning due to its versatility, interpretability, and strong predictive power across diverse domains (Schonlau & Zou, 2020; Liu et al., 2012; Denisko & Hoffman, 2018; Murphy & Moore, 2019; Segal, 2004).



1.2 Traditional Predictive Relationships and Modeling Algorithm of Carbon Dioxide:

1.2.1 Direct Correlation: Empirical research in Azerbaijan has shown a significant long-term association between MVA and CO₂ emissions per capita. Any changes in MVA lead to changes in CO₂ emissions levels; whether that change is toward rising or declining, the end points are both linked. Accordingly, Johansen cointegration analysis has been applied, confirming that changes in MVA are closely tied to emissions trends over time. And deviations from this relationship tend to self-correct, indicating a stable predictive link (Hasanov et al., 2025).

1.2.2 Sectoral and Regional Variations: In heavy industrial regions, industrial value added has been identified as the most influential positive driver of CO₂ emissions. That is why it surpasses factors like industrial structure and energy intensity. The scenario of modeling usage by the researcher reveals that emission peaks, but it has been proven that trends can be forecasted by analyzing changes in value added alongside other variables. Industrial value added serves better than industrial structure for predicting CO₂ levels (Duan et al., 2022).

1.2.3 Global Value Chains: This concept does not just calculate the carbon footprint from the final product. It calculates the carbon footprint from the entire chain that went into the product globally. It is using multi-regional input-output models to trace CO₂ emissions along global value chains. This has allowed for the estimation of emissions per unit of value added at country and sector levels. That is why we can say this approach helps quantify the environmental cost of manufacturing growth and at the same time supports more accurate cross-country predictions (Meng et al., 2014).

1.2.4 Machine Learning and Optimization: Most recently in the iron and steel sector, advanced machine learning algorithms have been used to forecast CO₂ emissions based on manufacturing output. This technology has helped in achieving high accuracy even with limited data. Lack of or limits of the data points are no longer a concern (Francisco et al., 2024).

1.2.5 AI in Additive Manufacturing: Artificial intelligence models such as XGBoost have been successfully applied to predict CO₂ emissions. It works from process parameters and value added in additive manufacturing to highlighting the potential for data-driven emission forecasting (Hauck et al., 2025).

Table 1 Summary Table of Most Recent and Traditional Predictive Relationships and Modeling of Carbon Dioxide		
Approach/ Context	Key Finding	Citations
National-level econometric	Strong long-term link between MVA and CO ₂ emissions	(Hasanov et al., 2025)
Sectoral scenario modeling	Industrial value added is top driver of emissions	(Duan et al., 2022)
Global value chain analysis	Emissions per unit value added can be systematically estimated	(Meng et al., 2014)
Machine learning	Accurate emission forecasts from manufacturing output data	(Francisco et al., 2024) (Hauck et al., 2025)
Source: Made by the Authors		



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2. Research Questions:

The purpose of conducting this research is to find the answer to two major questions as follows:

- 1- How much do CO₂ changes when there is a change in manufacturing value added?
- 2- What will the CO₂ emissions likely be in the future based on the changes?

3. Research Primary Objective:

We have set three primary objects for this study as follows:

The first objective is to measure the elasticity of CO₂ emissions with respect to manufacturing value added. We have set out to do so because we believe there is an understanding of the causal impact of industrial activity on emissions. We need to identify it. The second objective is developing a predictive model that is capable of forecasting future emissions based on manufacturing trends. And the third and final objective is to provide policy-relevant insights for emission reduction strategies and climate planning through both causal understanding and forecasting capability to create a more sustainable environment.

4. University Contributions to SDG Achievement

The achievement of SDG is an ongoing challenge. Universities tackle SDGs through separate functions and domains of activation. Their roles and relevance heavily depend on the local context and the emphasis put on cross-/interdisciplinary integration.

1-Problem Solving and Innovations: In supporting university-SDG integration, greatest attention is often put on the research component. Universities act as living laboratories for the application of real-time, evidence-based solutions for SDG challenges. Their research and development functions are critical, and as such, they are referred to as living laboratories for sustainable practices. (Purcell et al., 2019; Perović et al., 2025; Filho et al., 2024; Alawneh et al., 2021).

2- Education and Capacity Building: Universities are expected to prepare the coming generations of leaders and professionals to mitigate challenges on a global scale toward a more sustainable future. Curricula as a tool for transformative SDG implementation are becoming fundamental to fostering relevant global competencies (Kioupi & Voulvoulis, 2020; Sribanasarn et al., 2025; Filho et al., 2024).

3- Community and Stakeholder Engagement: The collaboration of universities with industry, government, and civil society is an example of the stakeholders' efforts alongside the university to enhance and scale sustainable practices (Purcell et al., 2019; Blasco et al., 2020; Valdez et al., 2024; Guerrero & Lira, 2023).

4-Institutional Operations: Reflecting on universities, model countries with strong policies on sustainable development SDG 12 and SDG 13 are targets of formal reports on responsible consumption and climate action (Perović et al., 2025; Alawneh et al., 2021; Sribanasarn et al., 2025).

4. Literature Review:



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The connection between manufacturing value-added calculation and carbon dioxide emissions is systematic and studiously documented in the manufacturing industry. The model suggested that value-added manufacturing continues to be a major factor influencing the carbon emissions. An attempt to compute the pattern of emissions caused by manufacturing growth demonstrates growth in emissions over years. The value-added manufacturing expansion in manufacturing resulted in more production of carbon emissions. However, the rate of such expansion is not being addressed by its scale. It has proved it only and later on cited even something bigger than manufacturing value added. The study has looked at if it is possible to increase the economic activity without increasing the carbon dioxide, and sadly every time manufacturing outputs have been increased, pollution has increased as well. The relationship is very well established. (Jin & Han, 2021). Furthermore, another study has identified the relationship, but it describes it as industrial value added. This used extensive data from 102 countries, and the study dates ranged from the year 1990 to 2015. Such a time series is huge, and there are a lot of data points. The magnificence of this study is in its categorization of countries and its relationship study between CO₂ and industrial value added. It says the poorer the country, the stronger the relationship. Meaning in poor countries this relationship is very clear and significant. And in rich or developed countries, such relationships are weak. It concluded that this is due to the use of clean energy. Developed countries from 1990 have slowly adopted the use of clean sources of power. This is why, sometimes, a high rate of industrial value has been spotted without an increase in carbon dioxide. (Jebli et al., 2020). Furthermore, studies were conducted regarding manufacturing value added and its linkage to carbon expansion, and it came out positive. This time it showed that manufacturing added value and industrial value added are similar metrics in terms of their effect on the level of carbon levels. They explained the claim through a formula that can be calculated that goes by the concept that more production size-wise and money-wise means more carbon level. There is more; the study claimed that not all sectors act like this. This claim put a pause into using the metric in its general form, because you cannot generalize the metric over the entire nation or a country. Some industries require a large scale of added value, but they have a low carbon footprint. The other end is the same; some sectors need to provide less value added. However, the scale of carbon is large enough that it could put the entire nation into a case of environmental catastrophe. The point was made clear that there is a connection, but it has to be sector-wise, not taking it in its general form. We have to be specific regarding what sector we are referring to; otherwise, the number will be inflated. (Xu et al., 2023) Another important study that was conducted in 2022 has revealed some interesting facts. It said there is a direct connection between manufacturing value added and carbon levels. The research examined 44 countries over 15 years, from 2000 to 2015, and found dramatic differences in emissions levels. The study found that every 1% increase in industry's share of gross domestic production has made carbon emissions per person increase by 0.3%. Paying close attention to this study, we can see that they focused on the industry. This study used gross domestic production as a proxy for industrial value added. Still, this can be too generalized, yet it is very close to being seen as sector-wise. It categorized the economy into industry and found the heating industry, meaning any industry that works with heating elements, does contribute to a larger scale of carbon level rise, and manufacturing value added does not give the full picture. The carbon level rises bigger than what we can calculate through some metrics. Such an industry, if it were stopped, could save the country from expenses in another sector. The environmental sector is one example. The methodology that was used to support these claims was panel data. And they used another model called lagged variable to predict the emission from other used variables such as manufacturing value added. (Mentel et al., 2022). We can see from the literature review table that there is a clear linkage between carbon level and manufacturing value added. The overwhelming majority of the studies have used manufacturing value added as a metric to predict the level of CO₂. Some have used the linear regression method; others have adopted the use of models that are more advanced. The bottom line of these studies was to demonstrate the superiority of each methodology in predicting and assessing the level of carbon dioxide. It's very hard to determine which one has more accuracy, yet the end results are clear from all the used papers that we have added a new line to the knowledge of model-based predictions and effects proxy and more direct metrics. It has been noted that all literature has used very advanced methodology in terms of study objective. This diverse methodological approach is the result of a case-by-case objective. At the end it has been established that all methods have their own benefits and drawbacks.

5.1 Identified Research Gaps:

Despite the progress that was made based on the literature review, three critical gaps remain. First, no



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study has directly compared traditional regression with machine learning approaches using identical datasets for CO₂-MVA data sets. Secondly, existing research lacks comprehensive global analysis covering both developed and developing countries in a single framework.

Table 2 : Summary of Literature Review

Author Names	Year	Title	Methodology	Results Summary	Relationship with CO2
Baoling Jin, Ying Han	2021	Influencing Factors and Decoupling Analysis of Carbon Emissions in China's Manufacturing Industry	Generalized Division Index Model (GDIM)	manufacturing carbon emissions are rising, with heavy industry as the main contributor.	Industrial value added is a driving force of carbon emissions.
Mehdi Ben Jebli, Sahbi Farhanib, Khaled Guesmi	2020	Renewable energy, CO2 emissions and value added: Empirical evidence from countries with different income levels	Generalized Method of Moments (GMM) and Granger causality test	Renewable energy use decreases CO2 emissions in most countries.	The industrial sector is responsible for a large share of global energy consumption and CO2 emissions.
Hua Xu, Bin Xia, Shumin Jiang	2023	The Impact of Industrial Added Value on Energy Consumption and Carbon Dioxide Emissions a case study of China	Multi-objective, linear programming model	Increased industrial value leads to increased CO2 emissions	Industrial added value has a strong positive correlation with CO2 emissions.
Urszula Mentel, Elżbieta Wolanin, Mansur Eshov, Raufhon Salahodjaev	2022	Industrialization and CO2 Emissions in Sub-Saharan Africa: The mitigating role of renewable electricity	Two-step system Generalized Method of Moments (GMM) estimator	The share of industry in GDP positively impacts CO2 emissions; renewable electricity can reduce this effect.	The share of industry in GDP (a proxy for industrial value added) has a significant positive impact on CO2 emissions.

Source: Made by the Authors

6. Carbon Intensity Framework

6.1 Conceptual Foundation



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We justify our use of carbon intensity as a metric of CO₂ emissions per value added of output in a given period, as it serves a pivotal purpose in determining the environmental efficiency of production activities in a given country. Unlike absolute emissions of any given greenhouse gas, the carbon intensity of emissions metric allows for the analysis of emissions data at different stages of development with different economic structures. This facilitates the analysis of structural changes in the economy where economic growth is achieved with a lowered environmental burden per unit of output.

6.2 Policy Relevance

Our analysis of carbon intensity addresses the following three policy questions:

- 1- Efficiency Assessment: Which countries have greater output with lower emissions?
- 2- Decoupling Assessment: Where is it possible to have economic growth devoid of equivalent increases in emissions?
- 3- Efficiency Assessment: What are the opportunities for emissions reduction through efficiency as opposed to reduction of economic output?

6.3 Mathematical Framework

The carbon intensity relationship can be expressed as:

Carbon Intensity (CI) = CO₂ Emissions / Manufacturing Value Added

Where changes in CI over time indicate:

CI declining + MVA growing = Absolute Decoupling (Ideal Scenario)

CI declining + MVA stable = Efficiency Improvement

CI stable + MVA growing = Relative Coupling (Traditional Pattern)

CI increasing + MVA growing = Carbon Intensification (Unsustainable)

7. Research Hypotheses

Based on the literature review and research questions, we developed three main hypotheses:

- 1- (H1): There is a positive relationship between manufacturing value added and CO₂ emissions changes across countries. Supported by Jin & Han (2021) and Jebli et al. (2020)
- 2- (H2): The relationship between manufacturing value added and CO₂ emissions is less than proportional (elasticity < 1). Supported by Xu et al. (2023)
- 3- (H3): Machine learning models will provide more accurate predictions of CO₂ emissions than traditional linear regression methods. Supported by Francisco et al. (2024)

8. Methodology

This paper relies on a quantitative approach, with manufacturing value added being the independent variable and carbon dioxide being the dependent variable. The methodology selected for the paper is a combination of machine learning, specifically the random forest machine learning approach, in addition to a traditional method for more accuracy. The use of such a combination is selected to present to the scientific community the extent of the accuracy rate of one modern methodology alongside the traditional way. Consequently, we have used data sets of carbon emission in million tons and manufacturing value-added metrics as a driver. The point is to see the changes of carbon emission from manufacturing value added and perceive the accuracy of both methods in carbon emission from the driver data sets. We have used data of 123 countries ranging from 2000 to 2022 for both sets of data from World Bank's World Development Indicators (WDI) database. Both data sets were unified, and missing values were cleaned. Furthermore, random forest with log-transformed data was applied to help normalize skewed data, making patterns more accessible for the random forest algorithm. This way random forest will be robust to data that are nonlinear or do not pass stationary tests. It is less sensitive to assumptions about data distribution and can handle both raw and transformed features effectively. Random Forest with log-transformed data generally provides higher predictive accuracy (Schonlau & Zou, 2020; Mushagalusa et al., 2022). The second method selected was known as simple linear regression with differenced and log-transformed data, as it handles both not normally distributed data and data that are non-stationary. As such, linear regression remains highly interpretable, and transformations can make coefficients meaningful. Such transformation will detect the linearity of the data sets. (Robinson et al., 2017) As for the steps in creating this papers algorithm we have applied the steps set by Matthias Schonlau, Rosie Yuyan Zou. The steps are in general



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data preparation, bootstrap sampling, tree construction and aggregation, and model evaluation (Schonlau & Zou, 2020). For the actual coding of the algorithm the writers have done all the coding as per the steps. The algorithm code is available for usage. The writers have used split ration and training ration of an 80 to 20 ratio. We implemented temporal validation using TimeSeriesSplit for cross-validation and a chronological split with training period 2001-2016 and test period 2017-2020 (last 4 years held out), ensuring no data leakage by training only on historical data. The model incorporates nine key features engineered from the raw data. These include economic variables (Log_MVA, MVA_Growth), temporal trends (Year_Trend, Year_Squared), efficiency measures (CO₂ Intensity_Change), and a lagged CO₂ variable (CO₂_lag1) to account for emission persistence. As for the hyperparamters we used it without tuning. Fixed hyperparameters without any tuning: `pythonacademic_rf = RandomForestRegressor(n_estimators=100, max_depth=8, min_samples_split=10, min_samples_leaf=5, max_features='sqrt', random_state=42)`. The code of this model is available in github free of charge for researchers who are willing to further expand this model. The three tables explain most of the methodology in the paper.

Table 3: Random Forest Settings	
Setting	Value
Number of trees	100
Maximum tree depth	8
Minimum samples to split	10
Minimum samples per leaf	5
Features per split	sqrt
Random seed	42
Source: Made by the Authors	

Table 4: Model Variables	
Variable	Description
Log_MVA	Manufacturing value (log scale)
MVA_Growth	Manufacturing growth rate
MVA_Change_Rate	Rate of manufacturing change
CO ₂ _Intensity_Change	Change in CO ₂ per manufacturing unit
Year_Trend	Time trend
Year_Squared	Non-linear time trend
MVA_Time_Interaction	Manufacturing × time interaction
MVA_Relative	Relative manufacturing position
CO ₂ _lag1	Previous year CO ₂ emissions
Source: Made by the Authors	

Component	Details
Countries	123
Time period	2001-2020
Total observations	2,454
Training period	2001-2016
Testing period	2017-2020
Cross-validation	5-fold time series
Target variable	Log(CO ₂ emissions)
Source: Made by the Authors	

9. The Results

9.1 Linear Regression Results:

This model directly measures the relationship between the rate of change in manufacturing and the rate of change in emissions.

Metric	Value	Interpretation
Coefficient (diff_log_MFG)	0.5936	For every 1% change in manufacturing, CO ₂ changes by 0.59%.
Intercept	0.0204	The baseline rate of change when manufacturing change is zero.
R-squared (R ²)	0.4577	The model explains 45.8% of the variance in emission changes.
Mean Squared Error (MSE)	0.0039	The average squared difference between actual and predicted values.
Source: Made by the Authors		

The linear regression model has revealed that there is a moderate but significant relationship between manufacturing and CO₂ emissions. The coefficient of 0.5936 indicates that for every 1% increase in manufacturing value added, there is an increase of approximately 0.59% of CO₂ emissions. This has demonstrated that there is a sub-unitary elasticity, which suggests improving efficiency over time. This model has explained 45.8% of the variance in emission changes with its $R^2 = 0.4577$. This is convincing for environmental-economic relationships because the accuracy is in the low mean squared error (0.0039), which confirmed the rate of accurate predictions. The intercept of 0.0204 reveals a baseline 2% annual CO₂ growth rate independent of manufacturing changes; this is likely reflecting other trends.

9.2 Random Forest Results:

Both below tables of the Random Forest model have demonstrated some predictive capability. We can see the model has achieved 94.3% accuracy on unseen test data (2017-2020) and 91.8% average performance during cross-validation. These numbers show that this model has both high accuracy and model stability. In addition to that, manufacturing-related features collectively contribute 40.2% importance. This is also confirming that manufacturing is the key economic driver of emissions. At the same time, it is capturing that the model successfully captures the complex interactions between economic activity, temporal trends, and emission patterns for accurate forecasting.



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Table 7: Model Performance	
Metric	Result
Cross-validation R ²	91.8%
Test R ²	94.3%
Standard deviation	±7.1%
RMSE	0.564
Source: Made by the Authors	

Table 8 summarizes the performance and key findings of the more complex Random Forest model		
Metric	Value	Interpretation
Cross-Validation R ²	0.918 (91.8%)	Average performance on training data, indicating high accuracy and stability.
Test Set R ²	0.943 (94.3%)	Performance on unseen data (2017-2020), demonstrating strong predictive power.
Manufacturing Importance	40.2%	Total importance of all manufacturing-related features, showing its key role.
Source: Made by the Authors		

Table 9 of Model Importance by Feature Category		
Category	Total Importance	Academic Interpretation
Primary Driver CO2 (Lag)	58.3%	The baseline momentum of emissions, acting as the most important single predictor for the current year. (Emission Persistence)
Key Economic Drivers (MVA)	40.2%	The primary economic forces, led by manufacturing, that explain the dynamic changes in emissions from the baseline.
Secondary & Nuance	1.5%	Subtle, long-term, and non-linear factors that refine the model's predictions and offer insights into efficiency and global trends.
Source: Made by the Authors		

Rank	Variable	Importance
1	CO ₂ _lag1	58.3%
2	Log_MVA	35.7%
3	MVA_Time_Interaction	2.5%
4	MVA_Relative	1.1%
5	CO ₂ _Intensity_Change	0.9%
6	MVA_Change_Rate	0.5%
7	MVA_Growth	0.5%
8	Year_Squared	0.3%
9	Year_Trend	0.3%

Source: Made by the Authors

10. Discussion of Findings

10.1 Discussion of Results

The analysis reveals that there are some complementary insights from both modeling approaches. Each model has addressed some different aspects of the manufacturing and emissions relationship. The linear regression provided a clear causal understanding. And the random forest algorithm offered a much superior predictive capability. Both together are forming a comprehensive analytical framework for policy assessment and emission forecasting that would provide us with solutions toward more sustainable environmental practices. The linear regression's elasticity of 0.5936 represents a significant finding. This number is indicating that CO₂ emissions respond less than proportionally to manufacturing changes. It could be suggesting ongoing efficiency improvements in the manufacturing sector. The 45.8% variance of (R²) also demonstrates that manufacturing value added is a major driver of emission changes. Most importantly, the machine learning model predictive accuracy of 94.3% validates the presence of this strong driver. It shows that this number came from a learning algorithm that experienced the data set and ended up with such a number. The dominance of emission persistence (58.3% lagged feature) reflects realistic inertia in energy systems. This also shows that carbon emission does not change in a short span. That is why it's important to rely on previous years' data as well. The number (40.2%) confirms the manufacturing value-added role as the primary driver. This predictive performance enables reliable scenario planning and policy impact assessment for emission reduction strategies for a better sustainable future. Based on these results, we can say the first question was answered by a 1% increase in manufacturing value added leading to a 0.59% increase in CO₂ emissions. As for the second question for the forecasting framework, we can say future CO₂ emissions are predicted using 58.3% weight on previous year's emissions (persistence pattern), 40.2% weight on manufacturing factors (economic drivers), and 1.4% weight on temporal and efficiency trends (contextual adjustments).

10.2 Decoupling analysis and Subsequent Policies and Actions.

Evidence from our analysis of carbon intensity shows that relative decoupling is prevalent across the global manufacturing sector. This means that multiple countries achieved carbon driven declines while increasing the value added from manufacturing at the same time, which means that sustainable growth in manufacturing is possible. Countries which managed successful decoupling adopted key policy changes such as the improving energies of the rest of the manufacturing system with the electric driven manufacturing, low carbon fuel switching from fossil fuels to renewables, and the maintaining of the advanced manufacturing and cleaner production system technologies. This directly advances SDG 9 (Industry, Innovation and Infrastructure) in 'Pathways to Sustainable Industrialization' and SDG 13 (Climate Action) as it develops metrics to reduce emissions while maintaining growth. Universities and other academic institutions play a pivotal role regarding the disconnect in manufacturing decoupling by training engineers and policymakers on clean manufacturing technology, curating open datasets to support evidence based decision making, and creating decision aiding mechanisms such as predictive tools which



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provide insight on the effects of various decisions.

11. Hypothesis Testing

Based on the results of this study we can conclude the hypothesis testing of this paper as follow:

- 1- Regarding H1 it's a positive relationship. This is showing supported hypothesis. The linear regression coefficient of 0.5936 confirms a positive relationship between manufacturing value added and CO₂ emissions.
- 2- Regarding H2 it is showing less than proportional Elasticity < 1 . This is also supported hypothesis because the elasticity coefficient of 0.5936 is significantly less than 1.
- 3- Regarding H3 machine learning superiority is strongly supported because, Random Forest achieved 94.3% accuracy compared to linear regression's 45.8% (R^2).

12. Recommendations

Our first recommendation will be directed to policymakers, as it's proven that this paper's Random Forest model predicts emissions with 94.3% accuracy. Governments get benefits from the use of similar models to test different policies before implementing them. This helps avoid costly mistakes and improves policy effectiveness. The model also shows manufacturing accounts for 40.2% of emission changes. This tells decision makers that manufacturing value added is also a drive that needs to be overseen. At the same time, we are showing a way for companies to know ahead of time what will be expected when they increase the manufacturing value added with an accuracy of over 90%. Such a model will help companies and governments to set simulations while applying different policies. On such facts, we recommend them to make supportive decisions as per these models.

13. Limitations of this study

One of the major limitations of this study is not using a larger data set. We only use 123 countries due to limitations of the availability of the data. This model can handle all countries of the world. Finding one unified data set of the world's countries was very challenging, to the point that we could not handle the process of cleaning the data. The missing data in between years for world countries is very hard to manage. The second limitation is not categorizing the countries based on the level of their development. Some countries are far more developed than others. This will lead to the third limitation, and that is finding a process that would put developing and developed countries into different sections. Such division is very hard when we address the problem globally. We lose the option of having more than one country. The fourth limitation is the use of the time range that we selected. We took the data from 2000 to 2022, and we got the results. But we do not know how these results will remain as they are when we focus on predicting after the year 2022, as technology is changing rapidly. As to the same fourth limitation, let's not forget the challenges that are beyond the control of human beings. These are things like force majeure events. Any unexpected event could be categorized as force majeure, as humans cannot control it.

14. Conclusion:

Manufacturing value added is a robust predictor of CO₂ emissions across national, sectoral, and global contexts. The prediction accuracy of CO₂ improves when we use models that incorporate other metrics alongside the carbon footprint. The results are improved whilst having a robust, accurate model. Such a recipe serves as an insight to support sustainability policymakers and industry leaders in designing a sustainable structure that assesses the reduction strategies. We also showed the accuracy of the model and, at the same time, the level of drive's influence over the major feature of the study. We also proved that data-driven decisions can be achievable to a certain level. And it's vital to have a tool that simulates the use of scenarios before taking any actions.



Annex number 1:

SPSS Statistics - Augmented Dickey-Fuller Unit Root Test: Complete Results for All Countries

Analysis Overview

Sample Period: 2000-2022 | Total Countries: 123 | Test: ADF with constant

Null Hypothesis: Series has unit root (non-stationary) | Significance Level: 5%

Country/Region	CO2 Emissions (MT CO2e)				Manufacturing Value Added				
	ADF	Prob.	5% Crit.	Result	ADF	Prob.	5% Crit.	Result	
Albania	-7.261	0.000	0.000	-3.104	Stationary	1.591	0.998	-2.999	Non-stat
Algeria	2.829	1.000	-3.104	Non-stat	-2.683	0.077	-2.999	Non-stat	
Angola	-1.689	0.437	-3.005	Non-stat	-3.082	0.028	-3.104	Stationary	
Argentina	-2.392	0.144	-2.999	Non-stat	-0.976	0.762	-3.005	Non-stat	
Australia	-1.246	0.654	-2.999	Non-stat	-2.188	0.211	-3.069	Non-stat	
Austria	-3.108	0.026	-2.999	Stationary	1.809	0.998	-3.104	Non-stat	
Azerbaijan	2.637	0.999	-3.104	Non-stat	-1.399	0.583	-3.005	Non-stat	
Bangladesh	1.773	0.998	-3.104	Non-stat	4.154	1.000	-3.069	Non-stat	
Belarus	-1.860	0.351	-3.054	Non-stat	-2.107	0.242	-3.022	Non-stat	



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Belgium	-1.059	0.731	-2.99 9	Non-stat	-2.156	0.223	-2.99 9	Non-stat	
Bhutan	-0.730	0.839	-3.00 5	Non-stat	-1.808	0.377	-3.05 4	Non-stat	
Bolivia	-2.532	0.108	-3.10 4	Non-stat	-1.935	0.316	-3.10 4	Non-stat	
Bosnia and Herzegovina	-1.185	0.680	-3.10 4	Non-stat	2.780	1.000	-3.08 5	Non-stat	
Botswana	-1.120	0.707	-2.99 9	Non-stat	-1.944	0.312	-3.00 5	Non-stat	
Brazil	-1.852	0.355	-3.06 9	Non-stat	-1.562	0.503	-3.10 4	Non-stat	
Burkina Faso	2.814	1.000	-3.08 5	Non-stat	-0.393	0.911	-3.01 3	Non-stat	
Cambodia	2.811	1.000	-3.10 4	Non-stat	3.450	1.000	-3.01 3	Non-stat	
Cameroon	-0.906	0.786	-3.04 2	Non-stat	-1.456	0.555	-3.08 5	Non-stat	
Canada	-2.421	0.136	-2.99 9	Non-stat	-3.011	0.034	-3.03 1	Stationary	
Chad	0.748	0.991	-2.99 9	Non-stat	1.067	0.995	-3.15 5	Non-stat	
Chile	-1.722	0.420	-2.99 9	Non-stat	-1.577	0.495	-3.10 4	Non-stat	
China	-2.821	0.055	-3.10 4	Non-stat	-0.527	0.887	-3.18 9	Non-stat	
Colombia	-0.481	0.896	-3.00 5	Non-stat	-2.465	0.124	-3.04 2	Non-stat	



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Congo, Dem. Rep.	-1.360	0.601	-3.10 4	Non-stat	2.469	0.999	-3.01 3	Non-stat	
Costa Rica	1.309	0.997	-3.10 4	Non-stat	2.458	0.999	-2.99 9	Non-stat	
Cote d'Ivoire	-2.875	0.048	-3.10 4	Stationary	4.129	1.000	-3.08 5	Non-stat	
Croatia	-0.497	0.893	-3.10 4	Non-stat	0.972	0.994	-3.10 4	Non-stat	
Cuba	-0.089	0.951	-3.02 2	Non-stat	-10.111	0.000	-3.15 5	Stationary	
Cyprus	-2.108	0.241	-3.10 4	Non-stat	-1.855	0.354	-3.10 4	Non-stat	
Denmark	-4.310	0.000	-3.06 9	Stationary	2.830	1.000	-3.10 4	Non-stat	
Dominica	-3.128	0.025	-3.08 5	Stationary	-2.429	0.134	-2.99 9	Non-stat	
Ecuador	-1.958	0.305	-3.00 5	Non-stat	-1.033	0.741	-2.99 9	Non-stat	
Egypt, Arab Rep.	-1.692	0.435	-3.08 5	Non-stat	0.448	0.983	-3.10 4	Non-stat	
El Salvador	-2.181	0.213	-2.99 9	Non-stat	-0.052	0.954	-2.99 9	Non-stat	
Estonia	1.420	0.997	-3.10 4	Non-stat	3.615	1.000	-3.08 5	Non-stat	
Ethiopia	-0.955	0.769	-3.00 5	Non-stat	0.682	0.990	-3.08 5	Non-stat	
Euro area	0.490	0.985	-3.10 4	Non-stat	3.145	1.000	-3.10 4	Non-stat	



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Fiji	-4.287	0.001	-3.10 4	Stationary	-8.699	0.000	-3.10 4	Stationary	
France	-0.968	0.765	-3.00 5	Non-stat	-2.322	0.165	-2.99 9	Non-stat	
Gabon	-5.643	0.000	-3.08 5	Stationary	-1.129	0.703	-2.99 9	Non-stat	
Georgia	-5.603	0.000	-3.10 4	Stationary	-0.487	0.894	-3.08 5	Non-stat	
Germany	-2.989	0.036	-3.00 5	Stationary	0.821	0.992	-3.08 5	Non-stat	
Ghana	-0.293	0.927	-2.99 9	Non-stat	-0.626	0.865	-2.99 9	Non-stat	
Greece	-1.125	0.705	-2.99 9	Non-stat	-2.716	0.071	-3.06 9	Non-stat	
Grenada	-1.648	0.458	-2.99 9	Non-stat	2.040	0.999	-3.06 9	Non-stat	
Guatemala	-2.156	0.223	-3.10 4	Non-stat	0.223	0.974	-2.99 9	Non-stat	
Guinea-Bissau	-1.944	0.311	-2.99 9	Non-stat	2.282	0.999	-3.03 1	Non-stat	
Haiti	-1.665	0.449	-2.99 9	Non-stat	0.859	0.993	-3.02 2	Non-stat	
Honduras	-4.598	0.000	-3.08 5	Stationary	0.521	0.986	-3.04 2	Non-stat	
Hong Kong SAR, China	-2.243	0.191	-3.05 4	Non-stat	-4.694	0.000	-3.05 4	Stationary	
Hungary	0.312	0.978	-3.10 4	Non-stat	-1.962	0.303	-3.01 3	Non-stat	



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Iceland	-2.776	0.062	-3.04 2	Non-stat	0.308	0.978	-3.01 3	Non-stat	
India	-0.295	0.926	-3.06 9	Non-stat	-3.156	0.023	-3.10 4	Stationary	
Indonesia	-2.061	0.261	-3.10 4	Non-stat	-1.053	0.733	-2.99 9	Non-stat	
Iran, Islamic Rep.	-3.895	0.002	-3.10 4	Stationary	-1.673	0.445	-3.00 5	Non-stat	
Iraq	1.489	0.998	-3.04 2	Non-stat	-1.126	0.705	-3.10 4	Non-stat	
Ireland	-3.421	0.010	-3.10 4	Stationary	-0.302	0.925	-2.99 9	Non-stat	
Italy	-0.111	0.948	-3.10 4	Non-stat	1.584	0.998	-3.10 4	Non-stat	
Jamaica	-2.091	0.248	-3.06 9	Non-stat	0.084	0.965	-3.10 4	Non-stat	
Japan	-1.901	0.332	-3.10 4	Non-stat	-1.943	0.312	-3.12 7	Non-stat	
Jordan	-0.827	0.811	-3.08 5	Non-stat	-0.709	0.844	-2.99 9	Non-stat	
Kazakhstan	0.065	0.964	-3.05 4	Non-stat	-3.540	0.007	-3.10 4	Stationary	
Kenya	0.418	0.982	-3.05 4	Non-stat	-1.810	0.376	-3.01 3	Non-stat	
Korea	-0.889	0.792	-3.10 4	Non-stat	-2.331	0.162	-3.10 4	Non-stat	
Kuwait	-2.607	0.092	-3.10 4	Non-stat	-1.731	0.415	-3.10 4	Non-stat	



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Latvia	-4.354	0.000	-3.10 4	Stationary	-0.910	0.785	-2.99 9	Non-stat	
Lebanon	-1.088	0.720	-3.00 5	Non-stat	-2.141	0.229	-3.12 7	Non-stat	
Lesotho	-1.920	0.323	-2.99 9	Non-stat	-1.949	0.310	-3.10 4	Non-stat	
Lithuania	-2.895	0.046	-3.00 5	Stationary	-2.231	0.195	-3.10 4	Non-stat	
Luxembourg	-2.130	0.233	-2.99 9	Non-stat	-2.604	0.092	-2.99 9	Non-stat	
Malaysia	0.941	0.994	-3.10 4	Non-stat	-2.057	0.262	-3.10 4	Non-stat	
Malta	-1.135	0.701	-3.10 4	Non-stat	-0.423	0.906	-3.10 4	Non-stat	
Mexico	0.432	0.983	-2.99 9	Non-stat	0.508	0.985	-2.99 9	Non-stat	
Moldova	-1.257	0.649	-2.99 9	Non-stat	-2.491	0.118	-3.10 4	Non-stat	
Mongolia	2.396	0.999	-3.06 9	Non-stat	-0.902	0.787	-3.06 9	Non-stat	
Morocco	-3.226	0.019	-2.99 9	Stationary	1.709	0.998	-3.10 4	Non-stat	
Mozambique	-1.969	0.300	-2.99 9	Non-stat	-2.747	0.066	-3.02 2	Non-stat	
Namibia	-0.704	0.846	-2.99 9	Non-stat	-2.234	0.194	-3.00 5	Non-stat	
Nepal	0.048	0.962	-2.99 9	Non-stat	0.268	0.976	-3.08 5	Non-stat	



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Netherlands	0.536	0.986	-3.06 9	Non-stat	3.083	1.000	-3.08 5	Non-stat	
New Zealand	-3.260	0.017	-3.10 4	Stationary	-1.801	0.380	-3.08 5	Non-stat	
Nicaragua	-1.546	0.511	-3.00 5	Non-stat	-0.132	0.946	-3.05 4	Non-stat	
Niger	0.556	0.987	-2.99 9	Non-stat	-1.492	0.537	-3.10 4	Non-stat	
Nigeria	1.754	0.998	-3.02 2	Non-stat	-0.440	0.903	-3.05 4	Non-stat	
North America	-1.709	0.427	-3.10 4	Non-stat	0.193	0.972	-3.03 1	Non-stat	
North Macedonia	-2.384	0.146	-3.10 4	Non-stat	0.048	0.962	-3.02 2	Non-stat	
Norway	-2.885	0.047	-2.99 9	Stationary	-2.174	0.216	-2.99 9	Non-stat	
Oman	-1.065	0.729	-3.01 3	Non-stat	-1.225	0.663	-3.00 5	Non-stat	
Pakistan	-0.993	0.756	-2.99 9	Non-stat	-1.439	0.564	-3.01 3	Non-stat	
Panama	-2.918	0.043	-3.05 4	Stationary	-2.917	0.043	-3.10 4	Stationary	
Paraguay	-1.596	0.486	-3.10 4	Non-stat	-1.320	0.620	-3.01 3	Non-stat	
Peru	-0.200	0.939	-3.00 5	Non-stat	-1.684	0.439	-3.02 2	Non-stat	
Philippines	4.252	1.000	-3.10 4	Non-stat	-1.106	0.713	-3.00 5	Non-stat	



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Poland	-2.153	0.224	-3.10 4	Non-stat	3.474	1.000	-3.10 4	Non-stat	
Portugal	-1.043	0.737	-2.99 9	Non-stat	1.522	0.998	-3.10 4	Non-stat	
Puerto Rico	-1.401	0.582	-3.10 4	Non-stat	0.064	0.964	-3.10 4	Non-stat	
Qatar	-0.954	0.770	-3.00 5	Non-stat	-1.329	0.616	-3.10 4	Non-stat	
Romania	-9.605	0.000	-3.08 5	Stationary	-1.307	0.626	-3.08 5	Non-stat	
Russian Federation	-1.407	0.579	-2.99 9	Non-stat	-0.872	0.797	-3.08 5	Non-stat	
Rwanda	0.093	0.966	-3.10 4	Non-stat	1.988	0.999	-3.10 4	Non-stat	
Saudi Arabia	-2.333	0.162	-2.99 9	Non-stat	1.863	0.998	-3.01 3	Non-stat	
Senegal	-0.340	0.920	-2.99 9	Non-stat	0.510	0.985	-3.10 4	Non-stat	
Sierra Leone	-1.168	0.687	-3.10 4	Non-stat	-0.328	0.922	-2.99 9	Non-stat	
Singapore	-0.444	0.903	-3.02 2	Non-stat	0.701	0.990	-3.10 4	Non-stat	
Slovenia	-2.041	0.269	-3.00 5	Non-stat	2.296	0.999	-3.10 4	Non-stat	
South Africa	-2.820	0.056	-2.99 9	Non-stat	-3.005	0.035	-3.10 4	Stationary	
South Asia	-1.558	0.505	-3.05 4	Non-stat	-1.527	0.520	-3.10 4	Non-stat	



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Spain	-1.931	0.318	-3.10 4	Non-stat	-2.218	0.200	-2.99 9	Non-stat	
Sri Lanka	3.095	1.000	-3.10 4	Non-stat	-1.611	0.478	-3.00 5	Non-stat	
Sweden	-3.473	0.009	-2.99 9	Stationary	-2.159	0.221	-2.99 9	Non-stat	
Switzerland	-0.332	0.921	-3.10 4	Non-stat	-1.669	0.447	-3.10 4	Non-stat	
Tanzania	0.253	0.975	-2.99 9	Non-stat	1.057	0.995	-2.99 9	Non-stat	
Thailand	0.273	0.976	-3.10 4	Non-stat	-1.509	0.529	-2.99 9	Non-stat	
Tunisia	-2.477	0.121	-2.99 9	Non-stat	0.573	0.987	-3.10 4	Non-stat	
Turkiye	-1.552	0.508	-3.10 4	Non-stat	-2.184	0.212	-3.10 4	Non-stat	
Uganda	2.198	0.999	-3.10 4	Non-stat	-0.600	0.871	-2.99 9	Non-stat	
Ukraine	-0.377	0.914	-3.03 1	Non-stat	-2.242	0.191	-2.99 9	Non-stat	
United Arab Emirates	-2.395	0.143	-3.04 2	Non-stat	-1.816	0.372	-3.10 4	Non-stat	
United Kingdom	-1.211	0.669	-3.03 1	Non-stat	-3.785	0.003	-3.04 2	Stationary	
United States	-1.323	0.618	-3.10 4	Non-stat	0.469	0.984	-3.03 1	Non-stat	
Uruguay	-2.622	0.089	-3.00 5	Non-stat	2.081	0.999	-3.10 4	Non-stat	



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Zambia	-0.050	0.954	-3.00 5	Non-stat	-2.713	0.072	-3.04 2	Non-stat	
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Summary Statistics

Variable	Total Countries	Stationary	Non-stationary
CO2 Emissions	123	18	105
Manufacturing VA	123	8	115



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