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RESEARCH

# Forecasting Sustainable Development Indicators Using XGBoost: Evidence from Brazil, Canada, China and India (2005–2023)

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## ABSTRACT

**PURPOSE:** This paper discusses the potential of machine learning to predict sustainable development indicators, gross domestic product (GDP), employment, and $CO_2$ emissions in Brazil, Canada, China and India to build a sustainable policy.

**DESIGN/METHODOLOGY/APPROACH:** An annual panel data (2005–2023) was employed to adopt a deductive and explanatory design. XGBoost (Extreme Gradient Boosting) is an algorithm that models nonlinear relationships and identifies important predictors based on macroeconomic, environmental, and policy variables.

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**FINDINGS:** XGBoost revealed high accuracy on GDP, and the balance of payments, climate policy, and green investment were some of the important predictors. $CO_2$ and employment forecasts were less certain because they were overfitted.

**ORIGINALITY/VALUE:** The paper identifies the application of machine learning to predict sustainable development, particularly economic modelling.

**RESEARCH LIMITATIONS/IMPLICATIONS:** There is an implication of overfitting and data limitations, which implies that higher-frequency data and hybrid models are required.

**PRACTICAL IMPLICATIONS:** The implication is based on evidence based policymaking in green investment planning and climate policy evaluation.

**KEYWORDS:** *XGBoost; Economic forecasting; Gross Domestic Product; Employment; $CO_2$ Emissions; Machine learning.*

## INTRODUCTION

Recently, green investment and renewable energy have been of primary interest in the context of sustainable economic growth. Financial and human resources are being committed more by governments, international organisations and private-sector businesses for the deployment of clean technologies, yet the quantifiable economic impacts of such investments are still unknown (Owusu and Acheampong, 2025). As an illustration, in 2023, the amount of solar and wind technology investment around the world increased by 75% to USD 200 billion which produced a benefit of 1% to 4% of Gross Domestic Product (GDP) in total exports in the United States, China, Europe and India (Wen *et al.*, 2025). This underscores the requirement for sound data and the prediction of nonlinear associations between renewable energy investments and macroeconomic results such as GDP, employment (EMP), innovation, and environmental performance. The traditional economic models do not reflect the complex and nonlinear associations that exist between renewable energy investments and the macroeconomic performance (United Nations Office for Project Services, 2021). There is a growing need to validate data-driven policymaking and sustainability planning, which requires computational and machine learning applications, such as XGBoost (Extreme Gradient Boosting) (Shash *et al.*, 2025). XGBoost is a gradient boosting tree model that enhances the accuracy of forecasting because it allows to account for nonlinear relationships, high dimensional data, collinearity, and missing values. This research paper compares XGBoost in predicting GDP, EMP and carbon dioxide ($CO_2$) emissions to determine its predictive power, its strengths and its ability to identify nonlinear relationships to offer a perspective in policy, investment and sustainable development planning.

# LITERATURE REVIEW

## Evolution of Sustainability Forecasting Research

As of 2021, it has involved research in the area of families, agriculture, policy, and methodological innovation. Lee *et al.* (2023) introduced the evidence of the pattern of uptake of renewable energy in Europe (EU) households between 2004 and 2019, with serious heterogeneity among the EU member states. This study also demonstrated how the socio-economic factors and national policies minimised or otherwise affected uptake trends and noted that there was fragmentation within the EU in terms of the rate at which the energy transition would be achieved. This was supported by the United Nations Office for Project Services (2021). It made a link between national urban policies and the climate action landscape and Sustainable Development Goals (SDGs), defining the role of governance structures in facilitating or hindering sustainability action. In the agricultural field, a Cobb-Douglas production function was used by Mahaboob *et al.* (2019) to derive a definition of sustainable farming outcomes, which found that input efficiency was a precursor to development, and argued that resource-use modelling may have a positive place in agrarian econometrics. Methodological work was also significant in the research domain. Lee *et al.* (2023) reported on the differences in predictive power among linear, random forest, and Adaptive Boosting regression models for non-traditional machining processes, providing a good starting point for discussion on the models, their reliability, and usability of methods in sustainability contexts (Scrieciu *et al.*, 2022).

In 2022, much of the research stemmed from cross-national comparisons and more rigorous methodological research. Scrieciu *et al.* (2022) conducted a comparative study of renewable energy research and investment in the EU and China, highlighting differences in the strategic frameworks underlying technology deployment. They discussed how scenario-development and forward scenario building could be used to further delineate policy change. Methodological issues were more prominent. Smith *et al.* (2024) analysed the modelling of knowledge in machine learning. Smith *et al.* (2024) studied ensemble models (random forest, XGBoost, and Natural Gradient Boosting) for slope prediction in landslides, indicating that model choice and predictive power could also be improved for predicting hillslope processes in landslides. In sustainability-resiliency assessment, Scrieciu *et al.* (2022) addressed the topic of model validation and helped to focus on the long-term reliability problems in the prediction. In a paper by Shpak *et al.* (2022), $CO_2$ emissions and macroeconomic output indicators were evaluated in an empirical manner, which proved that industrial development does affect environmental pollution.

The focus shifted to sustainability in the areas of labour, investment, and sectoral development in 2025 (Owusu and Acheampong, 2025). In a special issue of labour and policy, the International Labour Organisation (ILO) in the year 2021 reported on the links between sustainable development goals and labour-market results, which specifically examined labour-market transitions (ILO, 2021).

  

Owusu and Acheampong, (2025) have analysed the economic effects of the net-zero that the UK had undertaken and noted that there was no clarity on the processes and products to which the climate targets were influencing the macroeconomic performance. Treating the interdependence between renewable energy programs and environmental banking and financial investments, anticipated unintended effects on other viable resources.

Wen *et al.* (2025) emphasised OECD (Organisation for Economic Co-operation and Development) data on economic opportunity costs and gains in structure, predicting a low 0.2% growth in world activity by 2040 in the case of green transition (United Nations Office for Project Services, 2021). The development of green jobs in Germany, where the quantity of quoted jobs doubled, and the fact that growth is still being threatened by labour shortages, were also mentioned by Wen *et al.* (2025). Together, what has been identified in the labour force demonstrates that by mid-decade, sustainability research was no longer focusing on technology and policy, and was instead of focusing on labour markets, financial systems, and structural macroeconomic outcomes (Onabowale, 2024). So, it unveils a part of its importance in planning the economy in the long term.

## Research Gaps

Hybrid computational models (e.g., integrating statistical forecasting models such as Autoregressive Integrated Moving Average (ARIMA) with machine learning algorithms) may offer a better predictive accuracy of renewable energy (Noorunnahar *et al.*, 2023), but they are not commonly used in macroeconomic and sustainability prediction. The classic econometric models can also not easily explain non-linear and multidimensional interdependence among the most important sustainability variables including GDP, CO2 emissions, and EMP.

In comparison, machine learning techniques, especially gradient boosting algorithms such as XGBoost, have high potential in overcoming this limitation by being capable of using complex nonlinearities and cross-variable relationships. Nevertheless, as Teixeira *et al.* (2024) noted, a majority of current literature about renewable energy and economic forecasting is based on traditional methods, with few experiments being run with modern artificial intelligence instruments. That leaves the possibility of machine learning-based forecasting models that can be used to enhance the predictive quality and policy relevance of green investment, particularly with regards to evaluating the long-term economic and environmental effects of sustainable investments (Noorunnahar *et al.*, 2023).

Green energy and green investment markets are extremely sensitive to change in policies, technological advances, and macroeconomic shocks. However, most of the current forecasting models are based on fixed assumptions or linear time series trends that do not reflect structural nullification and changing market dynamics. According to Carrington (2024), sustainable growth forecasting has to include quick transitions across the globe and fluctuations associated with policies to be realistic and informative. In this respect, adaptive learning models like the XGBoost allow for more flexibility in the modelling of nonlinear and time-dependent relationships. Moreover, the integration of innovation and human capital dynamics into predictive models, as proposed by Apostol *et al.* (2022), might provide a better approach to make the forecasts more explainable and, at the same time, make the sustainability-based modelling more representative of the actual development of green economies.

## MATERIALS AND METHODS

### Data and Sources

In this paper, the annual panel data from years 2005-2023 was used. Brazil, Canada, China and India were analysed to estimate the relationships among green economic indicators and the main macroeconomic variables. The dataset included the variables of four main primary sources of data, namely the World Bank that included the GDP, EMP, CO2 emissions (CE) and green investments (GINV). Data was sourced from the International Renewable Energy Agency (IRENA), which provided renewable capacity (REC) measured in megawatts); the United Nations Environment Programme (UNEP), which provided climate policy (CP) indicators at the national level; and the International Monetary Fund (IMF), which provided variables such as the inflation rate (INF), with other variables being log-transformed while the Year variable was left untransformed. Such a descriptive statistics and visualisation approach as histograms were mainly used to investigate the distributions and check whether the outlying observations were present or not. Data analyses were performed by Python for data visualization. Machine learning and STATA 12 were used for the basic data checks.

### Machine Learning (XGBoost)

To conduct country-level prediction, each of the targets (GDP, CE, and EMP) was trained using XGBoost regression. Each target model included Year and the remaining indicators (GINV, REC, CP, INF, IR (interest rate), Balance of Payments (BOP), and, where applicable, GDP, CE, and EMP) as features. XGBoost optimises the following objective functions:

Where:

l: Loss Function

Ω: Regularisation Term

CV: Cross Validation

MSE: Mean Squared Error

The modelling was poor, which may have led to overfitting or been affected by a small sample size. The predictive performance could be improved through additional feature engineering or by including more macroeconomic indicators. Nevertheless, this analysis highlights the importance of all variables in the model, as they provide valuable insights into the role of green economic indicators in determining key macroeconomic results.

This study followed academic ethical standards, using only publicly available data with no human subjects or personal information. All analyses were conducted strictly for research purposes. No data was manipulated, fabricated, or falsified. The authors affirm full honesty, transparency, and integrity, with no plagiarism, or any form of unethical behaviour involved. (Source of data: https://data.worldbank.org/,https://www.irena.org/Data, https://www.unep.org/resources, https://data.imf.org/).

## RESULTS

The results found that the XGBoost model has a high predictive power for GDP in India ($R^2$ = 0.84), Canada ($R^2$ = 0.82) and China ($R^2$ = 0.89). This explains that the model is a good predictor of the actual economic growth trend. While the predictability of Brazil is very poorly rated, with a negative $R^2$ value (–0.16), this indicates that the model does not fit Brazil's GDP. Predicting $CO_2$ emissions and EMP is unreliable, as indicated by the substantial negative $R^2$ values in the majority of countries, meaning that the model performs worse than a random predictor. China was the exception, with the model predicting $CO_2$ emissions with a small-scale, legitimate positive $R^2$ (0.57), indicating a modest level of predictability in China's emissions data. For employment, the predictions are generally very poor, with negative $R^2$ values across the board, even though they can be predicted by something systematic with the variable set to roughly model the labour market. In summary, our findings suggest that XGBoost is a robust GDP forecasting mechanism, has some limited ability to predict $CO_2$ emissions depending on the circumstances, and does not provide an effective EMP forecasting model at all, calling for either a carefully constructed feature set approach or a combination of features and modelling.

Table 1 represents the performance of the XGBoost model, which demonstrates strong predictive capacity for GDP, effectively capturing the underlying temporal and structural patterns in India, China, and Canada but not for Brazil. The model is effective at predicting economic growth because the $R^2$ values are consistently high, especially in India and China.

The predictions for $CO_2$ emissions and EMP, on the other hand, appear to be overfitting, as they are almost perfectly accurate during training but yield negative $R^2$ values, indicating poor performance with new data. These results show that GDP is currently the most reliably modelled indicator. They also indicate that improvements in feature selection or the use of hybrid modelling techniques are required for $CO_2$ emissions and EMP forecasts.

The model's ability to accurately predict economic growth is highlighted by the consistently high $R^2$ values, particularly in India and China. Conversely, predictions for $CO_2$ emissions and EMP appear overfitted, showing near-perfect training accuracy but negative test $R^2$ values, meaning they do not generalise well to new data. Overall, these findings demonstrate that GDP is the most consistently predictable indicator under the current feature framework, while more careful feature selection or hybrid modelling approaches are needed for carbon emissions and EMP.

**Table 1: Performance of XGBoost Models on Key National Indicators across Countries**

| *Countries* | *GDP R2 (CV Score)* | *$CO_2$ emission R2 (CV Score)* | *EMP R2 (CV Score)* |
|---|---|---|---|
| India | 0.84 (0.030) | -0.75 (1.693) | -1.59 (0.043) |
| Brazil | -0.16 (0.005) | -6.11 (0.867) | -1.07 (0.036) |
| Canada | 0.82 (0.002) | -23.47 (2.777) | -2.24 (0.058) |
| China | 0.89 (0.046) | 0.57 (0.549) | -0.78 (0.016) |

*Source*: https://www.irena.org/Data, https://www.unep.org/resources, https://data.imf.org/

The CV score denotes the mean test MSE from k-fold cross-validation. For each target, features include Year and all remaining indicators: EMP, $CO_2$, GINV, REC, CP, INF, IR, and BOP. GDP is most predictably influenced by the BOP (0.202), climate policy (0.179), and GINV (0.137), with these factors being the strongest contributors to GDP growth. Inflation (0.116) and IR (0.097) also have an impact, while EMP, $CO_2$ emissions, and renewable energy capacity have weaker effects. Overall, this suggests that GDP prediction primarily centres on macroeconomic stability, policy contexts, and financial flows, while energy and environmental impacts are more peripheral.

$CO_2$ emissions are most predictively influenced by INF (0.196), GINV (0.169), and the BOP (0.132). IR (0.126) and REC (0.110) follow in terms of contribution. GDP itself (0.056) is the least predictive influence. This indicates that emissions are more a reflection of financial and investment processes (infrastructure) than of GDP or overall economic output.

EMP is most predictably influenced by the BOP (0.196), CP (0.154), and GINV (0.133). INF, IR, and REC all have predictive contributions of around 0.10, while $CO_2$ emissions (0.097) and GDP (0.063) are the least predictive influences.

This emphasises that trade and financial flows, as well as institutional policy contexts, are more important predictive influences on labour than production outputs. In a concluding assessment, the BOP and GINV are the two most predictive attributes for all three dependent variables, while GDP is only minimally predictive of $CO_2$ emissions and EMP.

Table 2 presents the feature importance scores from the XGBoost models for each dependent variable. For GDP prediction, BOP (0.202), CP (0.179), and GINV (0.137) were the most influential features. In the $CO_2$ emissions model, INF (0.196), GINV (0.169), and BOP (0.132) were key contributors. For EMP, BOP (0.196), CP (0.154), and GINV (0.133) were the most dominant features in terms of importance. These results consistently highlight the significance of macroeconomic indicators, such as the BOP and capital formation, in the models' predictive performance.

  

**Table 2: Feature Importance Score for Dependent Variables by XGBoost across all Countries**

| *Dependent Variable* | *Feature Importance* | *Score* |
|---|---|---|
| GDP | BOP | 0.202444 |
| | CP | 0.179274 |
| | GINV | 0.137085 |
| | INF | 0.115528 |
| | IR | 0.097416 |
| | Year | 0.085704 |
| | $CO_2$ emission | 0.07122 |
| | EMP | 0.067651 |
| | REC | 0.043679 |
| $CO_2$ Emissions | INF | 0.195973 |
| | GINV | 0.169271 |
| | BOP | 0.132101 |
| | IR | 0.125619 |
| | REC | 0.110226 |
| | CP | 0.074506 |
| | EMP | 0.071351 |
| | Year | 0.065007 |
| | GDP | 0.055945 |
| EMP | BOP | 0.196492 |
| | CP | 0.154156 |
| | GINV | 0.132976 |
| | INF | 0.104429 |
| | IR | 0.103159 |
| | REC | 0.098404 |
| | $CO_2$ emission | 0.0973 |
| | GDP | 0.06322 |
| | Year | 0.049865 |

*Source*: https://www.irena.org/Data, https://www.unep.org/resources, https://data.imf.org/

The hyperparameters set for the GDP model mean that caution is required when making changes. The tree is not very deep (it can only go three levels), and the learning rate is low (0.05). The model also uses full sampling for both features (colsample_bytree = 1) and observations (subsample = 1). This choice improves stability and generalisation, making the model less likely to overfit. However, if the relationships are not linear, it could result in underfitting.

The $CO_2$ emissions and EMP models, on the other hand, perform better when the parameters are more flexible, with a greater maximum depth (max_depth = 5) and lower subsampling rates (subsample = 0.8, colsample_bytree = 0.8). The $CO_2$ model has a higher learning rate (0.1), allowing it to adapt quickly to more complex relationships. The EMP model, however, maintains a low learning rate (0.05) for stability. These hyperparameter adjustments enable the models to better handle nonlinearities and interactions between variables, but they also increase the risk of overfitting.

This highlights the importance of carefully using cross-validation and/or regularisation to assess a model's predictive performance. Table 3 lists all the hyperparameters used for the XGBoost models corresponding to the dependent variables. The GDP model was easier to interpret because it had a max_depth of 3, a learning_rate of 0.05, and full sampling (colsample_bytree = 1, subsample = 1). In contrast, the EMP and $CO_2$ emissions models use deeper trees (max_depth = 5), lower subsampling rates (colsample_bytree = 0.8, subsample = 0.8), and different learning rates (0.1 for $CO_2$ emissions and 0.05 for EMP). These adjustments were made to accommodate the specific needs of each target and the requirements for regularisation.

**Table 3: Hyperparameters of XGBoost for Dependent Variables across all Countries**

| *Dependent Variable* | *Hyperparameter* | *Value* |
|---|---|---|
| GDP | colsample_bytree | 1 |
| | learning_rate | 0.05 |
| | max_depth | 3 |
| | n_estimators | 100 |
| | Subsample | 1 |
| | colsample_bytree | 0.8 |
| $CO_2$ Emissions | learning_rate | 0.1 |
| | max_depth | 5 |
| | n_estimators | 100 |
| | Subsample | 0.8 |
| | colsample_bytree | 0.8 |
| | learning_rate | 0.05 |
| EMP | max_depth | 5 |
| | n_estimators | 100 |
| | Subsample | 0.8 |

*Source*: https://www.irena.org/Data, https://www.unep.org/resources, https://data.imf.org/

The cross-validation output for GDP forecasting suggests that the in-sample results were promising, although generalisation was poor. The training mean squared error (MSE) averaged 0.0361, and the $R^2$ training value was very high at 0.9433, indicating that the model explained a significant amount of variance in the training data. The average test MSE increased to 0.8051, and the average test $R^2$ was negative (−0.4694), indicating that the model performed worse than a baseline predictor on average for all but one-fold. Specifically, fold 3 performed only slightly better than the baseline, with an average test $R^2$ of 0.1369.

The four folds with negative and unsatisfactory $R^2$ values confirmed that overfitting was an issue. The $CO_2$ emissions output exhibited a similar overfitting problem. The average training MSE was close to zero (0.0003), and the average training $R^2$ was close to 1 (0.9997), indicating an almost perfect fit on the training data. Test performance was poor, with an average test MSE of 1.1838 and a mean $R^2$ of −0.7351. As demonstrated in the results, the model memorised the training data but did not generalise well to the test data, primarily due to overfitting on noise in the training set, resulting in no meaningful predictive power on unseen data.

In the case of EMP, the results showed a consistent pattern. The average training MSE was 0.0004, and the average training $R^2$ (0.9876) indicated an appropriately fitted model on the training data. However, the out-of-sample (test) performance showed an average test MSE of 0.0414 and an average test $R^2$ of −0.6075. All folds yielded negative test $R^2$ values, indicating that the model likely suffered from consistent overfitting and did not generalise.

The cross-validation results revealed that across all measures, GDP, $CO_2$ emissions, and employment consistently suffer from overfitting. The models fit the training data well but failed to accurately predict trends in new cases. Future analyses should incorporate stronger regularisation, alternative modelling approaches, or different data filtering techniques to improve generalisability and forecasting reliability.

Table 4 reports the cross-validation results for XGBoost models predicting GDP, $CO_2$ emissions, and EMP across all countries. While the models achieved low training MSE and high training $R^2$ values (GDP: 0.94, $CO_2$ emissions: 0.9997, EMP: 0.9876 on average), the test $R^2$ values were largely negative for all variables (GDP: −0.47, $CO_2$ emissions: −0.73, EMP: −0.61 on average). This pattern highlights a strong fit on the training data but poor generalisation to test data, indicating overfitting across the models.

**Table 4: Cross-Validation Results for Dependent Variables by XGBoost across all Countries**

| *Dependent Variable* | *Fold* | *Train MSE* | *Test MSE* | *Train R2* | *Test R2* |
|---|---|---|---|---|---|
| GDP | 1 | 0.0345 | 0.5555 | 0.9525 | -1.3715 |
| | 2 | 0.0295 | 0.6732 | 0.9561 | -0.2746 |
| | 3 | 0.0491 | 0.6045 | 0.9217 | 0.1369 |
| | 4 | 0.0301 | 1.1208 | 0.9446 | -0.2289 |
| | 5 | 0.0372 | 1.0713 | 0.9414 | -0.6090 |
| | Mean | 0.0361 | 0.8051 | 0.9433 | -0.4694 |

| *Dependent Variable* | *Fold* | *Train MSE* | *Test MSE* | *Train R2* | *Test R2* |
|---|---|---|---|---|---|
| $CO_2$ Emissions | 1 | 0.0003 | 1.7494 | 0.9996 | -0.6829 |
| | 2 | 0.0002 | 0.7233 | 0.9998 | -1.0679 |
| | 3 | 0.0003 | 0.9761 | 0.9996 | -0.2479 |
| | 4 | 0.0002 | 1.5655 | 0.9997 | -0.5092 |
| | 5 | 0.0002 | 0.9049 | 0.9998 | -1.1673 |
| | Mean | 0.0003 | 1.1838 | 0.9997 | -0.7351 |
| | 1 | 0.0004 | 0.0253 | 0.9866 | -0.1728 |
| EMP | 2 | 0.0004 | 0.0429 | 0.9873 | -0.4325 |
| | 3 | 0.0003 | 0.0389 | 0.9888 | -0.9393 |
| | 4 | 0.0004 | 0.0393 | 0.9870 | -1.1425 |
| | 5 | 0.0003 | 0.0605 | 0.9881 | -0.3503 |
| | Mean | 0.0004 | 0.0414 | 0.9876 | -0.6075 |

*Source*: https://www.irena.org/Data, https://www.unep.org/resources, https://data.imf.org/

The results support the broader understanding that economic growth remains a central driver of sustainable development. In contrast, environmental and labour-related outcomes may require more nuanced modelling strategies to capture their complex interdependencies.

## DISCUSSION

Overall, the XGBoost modelling results were mixed across the three dependent variables. For GDP, the models predicted accurately, with consistently high $R^2$ values, especially in India and China. Feature-importance analysis showed that BOP, CP, and GINV were key contributors, reflecting economic theory that macroeconomic fundamentals and policy actions shape growth. The relatively simple GDP model, with shallow trees and low learning rates, effectively captured stable structural tendencies in the data.

The $CO_2$ emissions and EMP models were effectively overfitted. Training $R^2$ values were near one hundred percent, while test $R^2$ values were negative, indicating that the models were unable to generalise. $CO_2$ emissions and employment are particularly sensitive to broader structural and institutional dynamics. For instance, EMP is often influenced by labour market frictions, changes in demographics, and shifts in the sectoral composition of employment that are not accounted for in the predictors. $CO_2$ emissions are also affected by energy mixes, enforcement of regulatory regimes, and consumption patterns, which lie outside the scope of the macroeconomic measures used in this analysis. While the models utilised deeper trees and higher learning rates, even with hyperparameter tuning to improve regularisation, these approaches may have compounded overfitting issues.

  

The feature importance results are particularly relevant in the context of analysing factors influencing $CO_2$ emissions across countries. The BOP, CP, and GINV had some relevance across countries but the overwhelming importance of INF and GINV in predicting $CO_2$ suggests that economic-financial variables are more influential than direct environmental predictors. Future work should include fine-grained energy or sectoral variables. The EMP forecast follows a similar pattern, where the presence of BOP and CP highlights macro-level relationships. However, the poor test performance indicates the need to consider omitted variables, such as productivity, labour participation rates, or education, to model EMP comprehensively.

The cross-validation results confirmed that the models were over-tuned to the training data. Regarding GDP, the training $R^2$ values were high, while the average test $R^2$ was negative, indicating the model's limited robustness to country-specific behaviours. For log $CO_2$ emissions and EMP, generalisation was even worse, with test MSE values several orders of magnitude greater than the training errors. This suggests that feature engineering and hybrid modelling should be applied together. More specific indicators, such as energy intensity, sectoral employment composition, or technology adoption rates, could help improve generalisation. Hybrid models could combine the econometric appeal of traditional approaches with the flexibility of machine learning, allowing for structural dependencies while limiting overfitting.

To summarise, the findings suggest that GDP is much easier to model with the current feature set, as it is strongly linked to economic indicators. Environmental and labour market outputs are more complex to model. Future work will require additional explanatory variables, ensemble methods, and further testing of models, sampling techniques, and regularisation approaches to validate the findings and develop a more reliable method for accurately explaining and contextualising sustainable development indicators, thereby offering greater potential for policy derivation.

This study contributes to the growing literature on the predictive modelling of sustainable development by assessing the effectiveness of an advanced machine learning technique, the XGBoost algorithm, across key macroeconomic and environmental indicators in four major economies. Several key findings emerge, providing empirical insights into the complex interdependencies among GDP, EMP, $CO_2$ emissions, and the role of GINV strategies.

Our XGBoost model showed strong GDP predictive accuracy, especially for India and China, where $R^2$ exceeded 0.80 (India, China; see Table 1). In contrast, it performed poorly for $CO_2$ and EMP, yielding negative $R^2$ in Brazil ($CO_2$: –6.11; EMP: –1.07) and Canada ($CO_2$: –23.47; EMP: –2.24), reflecting overfitting risks. These results show that GDP forecasting is stable, but $CO_2$ and EMP require richer, context-specific or hybrid models integrating institutional policy and energy variables, with future work exploring collaborative and deep-learning approaches.

## CONCLUSIONS

This research assesses the use of XGBoost for predicting sustainable development indicators in India, Brazil, China, and Canada, demonstrating that no single model excels in every situation. XGBoost performs well in predicting GDP when sufficient data is available, but it performs poorly for $CO_2$ emissions and EMP due to overfitting and limited generalisation. Policy implications indicate that forecasting methods need to align with the quality of the data and the characteristics of the variables. Traditional models remain useful for economic planning, while modified machine learning models can improve $CO_2$ predictions when more information is incorporated. Future research should expand datasets, incorporate structural factors, and develop hybrid models to enhance forecasting precision and policy significance.

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