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Research Article

Sustainable Supply Chain Management: Assessing Environmental Impact Using Data Analytics

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ABSTRACT

Organizations have begun to use data-driven decision-making techniques in response to the rising significance of sustainability in supply chain management. To evaluate and improve the environmental impact of supply chains, this study examines the use of data analytics, in particular the use of sophisticated regression models. This study looks at how various supply chain processes including transportation, procurement, and production affect the environment and examines the sustainability measures. This study uses novel regression methods, termed as multivariate adaptive regression splines (MARS) as well as generalized additive models (GAMs), to show the non-linear relationship among the environmental factors and supply chain choices. The results show that these models help with sustainability performance predictions and that they can aid businesses in making eco-friendly supply chain choices. By combining sustainability objectives with data analytics to enhance supply chain environmental performance, this study contributes to the expanding body of knowledge.

Keywords: Data Analytics, Regression Models, Environmental Impact, Supply Chain Optimization, Sustainable Supply Chain Management (SSCM)

1. INTRODUCTION

Big data (BD), or massive amounts of data, are continuously produced as a result. A paradigm shift in corporate decision-making may be possible with the use of big data analytics (BDA). For BDA to work, "Big Data" as well as "Data Analytics" are important. The first component, "Big Data," describes the massive volume of data produced by industrial-strength technologies like barcodes, sensors, RFID, the Internet of Things (IoT), and so on. To analyse these enormous and complex datasets, "Data Analytics," uses cutting-edge technologies [1]. In the face of ambidexterity and industrial disruption, this research adds to the body of knowledge on data-driven supply chain management (SSCM) indicators. The SSCM method for managing information flows considers economic, social, and environmental factors to help people and organisations in the supply chain work together and cooperate [2].

This study looks into how skills in BDA, circular economy (CE), and sustainable supply chain (SSC) adaptability affect SSC's performance. The research yielded fascinating results from a survey of 320 manufacturing companies. According to this research, the BDA has no bearing on sustainable performance. The BDA promotes the implementation of CE protocols [3]. Another research focuses on enhancing sustainable performance (SP) through AI-driven BDA. Green supply chain cooperation (GSCC), environmental process integration (EPI), and sustainable manufacturing (SM) are responsible to enhance SP [4].

The benefits of BDA-AI in integrating supply chains as well as how it affects environmental performance, on the other hand, haven't been studied in depth very often. To address this shortcoming, a study positioned digital learning as a moderator for the green supply chain process and expanded the idea of organisational information processing to include BDA-AI. Using a structural equation modelling approach based on partial least squares regression, a conceptual model is constructed to evaluate data from 168 French hospitals [5]. There has to be more clarity on the impact of the circular economy on social sustainability, despite the fact that it is often adopted by developing country firms to attain carbon neutrality requirements. It has been noted that stakeholders, such as community stakeholders, are not always informed about the circular supply chain operations of the business [6].

Highlighting the crucial role of technology in improving sustainability, an article delves into the convergence of data-driven techniques with environmental risk management. This literature review on public-private partnerships, data quality issues, and other new developments includes a lot of different new ideas. Two examples are Machine Learning (ML) and using the IoT to keep an eye on the environment [7]. Another paper specifically presents an integrated data-driven method to address the existing difficulties. Utilising state-of-the-art AI methods, such as convolutional as well as recurrent neural networks fine-tuned using the Moth-flame Optimisation Algorithm (MFO), this work reliably forecast the amount of demand for automobile parts. This model obtains a remarkable accuracy rate of over 90% via empirical validation with Iranian car parts manufacturers [8].

Although supply chain analytics have made extensive use of classic regression models, these models often fail to capture the non-linearity along with complexity present in environmental data. There are limitations to the accuracy of sustainability evaluations due to a lack of adaptation to dynamic supply chain settings as well as a lack of integration of real-time data. Furthermore, past data alone cannot predict new environmental variables or delays in global supply chains. These restrictions call attention to the need for enhanced modeling methods that can handle real-time sustainability data and complicated, non-linear connections. Hence the contributions of this research are as follows:

- The study uses novel regression models, like MARS and GAMs, to look at the non- linear relationships in environmental impact data across different supply chains.
- Offers a data-driven approach to assess sustainability performance using data collected from the supply chain in real-time.
- Provides supply chain managers with practical advice on how to include environmental sustainability measures in their decision-making.
- Creates an R tool for supply chain practitioners to evaluate and improve sustainability metrics using regression analysis.
- Using performance metrics like R-squared, Root Mean Square Error (RMSE), and Akaike Information Criterion (AIC), assesses the proposed models' accuracy.

Here are the details of the work organization: Some existing approached related to SSCM research is given under Section 2. Section 3 discusses the details of the proposed methodology. Section 4 includes details on the research findings and comments, along with some limitations of the current study. Section 5 concludes the research, followed by the references.

2.LITERATURE REVIEW

Belhadi et al. [9] used organisational information-processing theory, to investigate how data analytics skills allow data-driven digital transformation, which in turn helps supply chains achieve a balance between reducing economic performance along with carbon emissions. The article delves into the idea of carbon transparency in the supply chain as well as how it might help alleviate doubts. The activity enhances both environmental sustainability (carbon reduction) and economic results. Incorporates carbon and economic performance into a mutually beneficial arrangement. Implements data analytics to provide visibility into the supply chain, which may improve decision-making. The restrictions include more real-world examples. The dataset likely includes actual data from supply chain activities, carbon emissions, and economic indicators.

Chaudhuri et al. [10] discussed about organisations that cultivate a data-driven culture by using Industry 4.0 apps. Organisational sustainability performance, product and process innovation, and the impact of this culture on these are also examined. The job encourages making decisions and introducing new ideas based on data. To gain an edge over the competition by enhancing organisational skills, Industry 4.0 technologies are essential. Make a linking between data culture and sustainable performance by putting an emphasis on sustainability. Research on the effects of Industry 4.0 on data-driven culture as well as sustainability is scarce. There is a lack of knowledge regarding the lasting impacts of these changes. Although not explicitly mentioned, the dataset likely includes case studies from companies using Industry 4.0 technologies.

Pasupuleti et al. [11] applied ML techniques like regression, clustering, classification along with time-series analysis to the historical data of a global retail firm. Logistics and inventory management are the primary areas of emphasis. The effort enhanced lead time efficiency by 12%. ML improved decision-making, leading to an 8% decrease in replenishment errors. This demonstrates that ML has the potential to transform the way major corporations manage their supply chains. The findings' limitations include that they are based on data from only one organisation, making it difficult to apply them to other sectors. The study primarily focusses on retail, so generalisations may not be applicable to other industries. The data set provided contains historical data from a global retail giant, including revenues, inventory levels, order fulfilment rates, and operating expenses.

Rekabi et al. [12] described in their proposal for a Green Blood Supply Chain (GBSC), they incorporate resilience measures and congestion in blood centres into a multi-echelon model with several objectives. They use a linear regression model to forecast blood demand. As a result of this study, blood supply chains see fewer price increases, shorter wait times, and less environmental harm. This study enhances the resilience of supply networks, thereby addressing significant issues such as blood shortages. Due to its reliance on potentially scalable linear programming approaches, the constraint is inefficient for instances of enormous sizes. Though not mentioned, the dataset most certainly contains information on the supply and demand for blood within healthcare systems.

Liu et al. [13] investigated how digitalisation, supply chain disruptions, economic growth along with FDI affect the development of environmental technologies in G7 countries using fixed-effects regression as well as Prais-Winsten regression with PCSEs. This study provides a deeper understanding of the interplay among digitalisation, supply chain disruptions, and sustainability technologies. This study holds significant implications for policymakers who aim to foster sustainable technological development and fortify supply chains. The study solely focusses on the G7 countries, making it unsuitable for cross-national comparisons. The study examines data from 1990 to 2020, which may not fully capture the most recent technological developments or upheavals. This study used the economic and supply chain data sets from the G7 countries from 1990 to 2020.

Nazari et al. [14] examined the environmental impact and transportation costs within the automobile industry's supply chain using descriptive-analytical research that uses time series forecasting, especially Narnet. This work optimises transportation expenses, which helps reduce system costs and environmental pollutants. There is an emphasis on sustainable supply chain intelligence in the car business, which stresses being environmentally responsible while still being cost-efficient. Drawbacks include an overemphasis on the car industry and a possible inability to extrapolate findings to other sectors. This study used an unnamed dataset that likely included transportation cost data from the automotive supply chain.

Chen et al. [15] defined the integration of AI with activity-based costing (ABC) systems in the field of cost accounting. This article examines the impact of AI-powered ABC on decision making, operational efficiency, and cost allocation. Better financial decision-making and operational efficiency are the results of the work's enhanced accuracy in cost allocations. The integration of AI can transform conventional cost accounting systems. The potential high cost of adopting artificial intelligence in ABC systems could pose a significant challenge for smaller businesses. There is no indication of the specific dataset used; it is likely case studies or organisational data pertaining to cost accounting. Table 1 shows the existing work review.

Table 1: Existing work Review

Papers and Authors	Methodology	Advantages	Limitations
Belhadi et al. [9]	Organizational information-processing theory, Data-driven digital transformation (Data analytics)	Increasing supply chain carbon transparency can increase economic performance and reduce carbon emissions.	Empirical evidence does not adequately support the precise circumstances for achieving the intended results.
Chaudhuri et al. [10]	Industry 4.0 applications, Data-driven culture analysis,	It promotes a data-driven culture throughout the organisation, speeds up	There is a dearth of research on the effects of Industry 4.0 on data-

	Organizational sustainability performance	decision-making and creativity, and might lead to a competitive edge.	driven culture and how it relates to sustainability performance.
Pasupuleti et al. [11]	ML algorithms (regression, classification, clustering, time series analysis)	This study have enhanced the responsiveness of the supply chain, proven improvements in lead time efficiency, and decreased mistake rates.	The policy is restricted to the particular setting of a global retail conglomerate and is not applicable to other sectors.
Rekabi et al. [12]	Multi-objective multi-echelon model, Linear regression for blood demand forecasting	It addresses the need to reduce prices, wait times, and environmental impact while also strengthening the supply chain.	The system is overly dependent on linear programming, which is inefficient when dealing with large-sized instances.
Liu et al. [13]	Fixed-effects regression, Prais-Winsten regression with PCSEs for supply chain and economic factor analysis	The article outlines the impact of foreign investment and digitalisation on the development of sustainable technologies.	Focusing on a historical timeframe (1990–2020) that may not be reflective of current developments, it is only available to G7 countries.
Nazari et al. [14]	Descriptive-analytical, Time series forecasting (Narnet) for transportation costs and pollution analysis	This information may help us better understand the environmental costs of the automotive industry's supply chains.	The focus on automotive firms limits its applicability to non-automotive sectors or international settings.
Chen et al. [15]	AI integrated with ABC systems	It enhances operational efficiency, decision-making, and the accuracy of cost allocation.	There are potential implementation difficulties for smaller businesses and a need for substantial investment in AI technologies.

3. PROPOSED METHODOLOGY

Beginning with data collection and ending with practical suggestions, the research process for evaluating environmental impact in supply chains using data analytics adheres to a systematic methodology. This study must first study transportation, manufacturing, and procurement processes, among others, for relevant environmental and supply chain metrics.

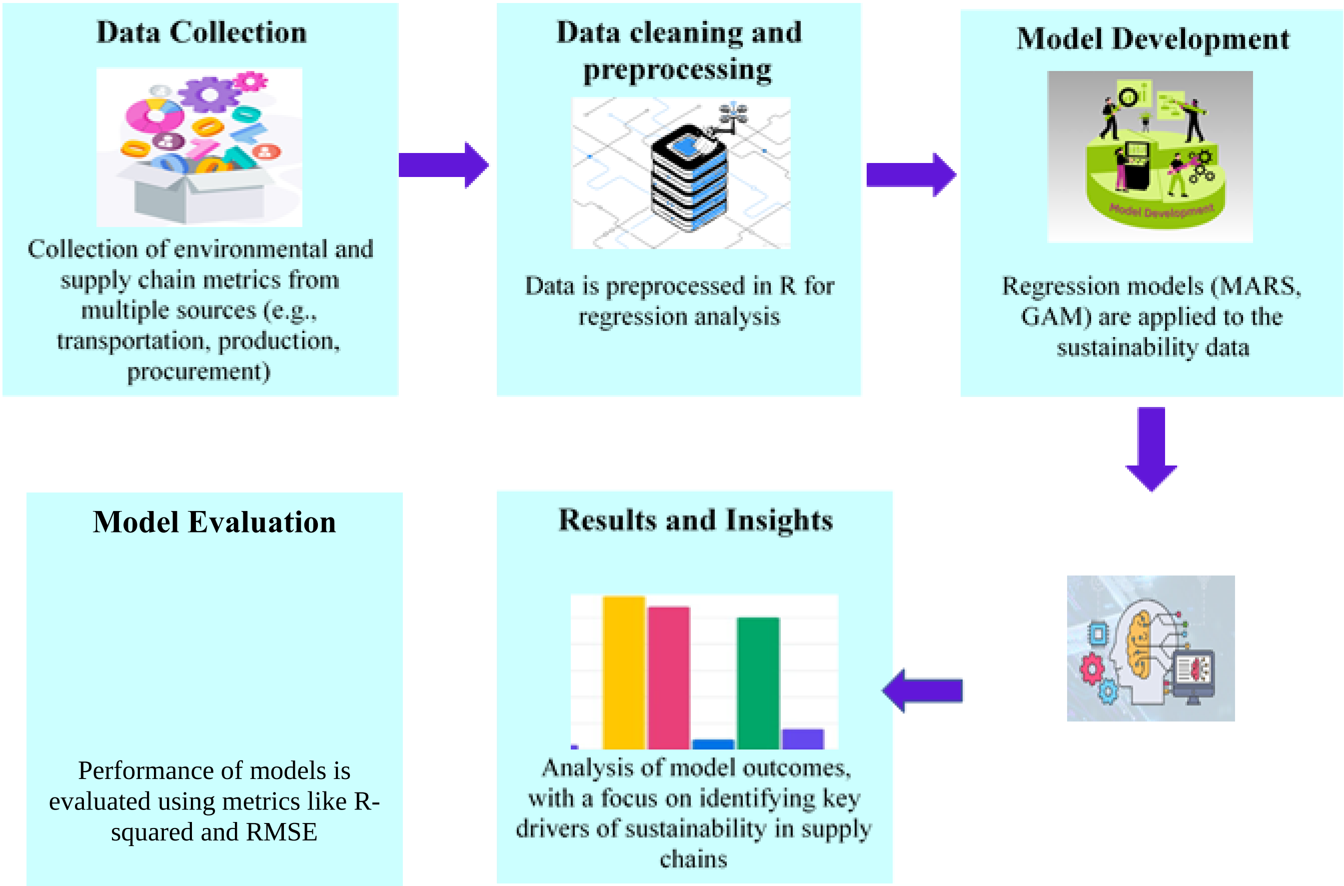


Figure 1: Flow of Research Work

Along with the sustainability metrics included the dataset further include statistics on energy usage, waste generation and carbon emissions. Following data collection, in R data cleaning and preprocessing is done to fix any outliers or missing values and prepare the data for regression analysis. Doing so guarantees that the dataset is suitable for model development in terms of accuracy and reliability. Applying GAMs and MARS frameworks to sustainability data is part of the model development process. These models are useful for figuring out the complex, non-linear connections between supply chain activities and their environment outcomes [16]. This study flow is shown in Figure 1.

3.1. Data Collection

This study is based on measurements collected from the supply chain and the environment. This study collect data from various sources, including production procedures, transportation logistics, and procurement operations. These data points typically include carbon emissions, energy consumption, transportation efficiency, waste generation, and other pertinent environmental metrics that aid in sustainability evaluations. The originality comes from the fact that it takes a comprehensive approach by including several sustainability criteria into different supply chain processes. Previous research has often focused on discrete processes, but this comprehensive data collection enables to capture a wider range of environmental influences. Data collection from various supply chain stages enables a more thorough understanding of where inefficiencies and environmental problems occur, which is essential for targeted sustainability solutions.

3.2. Data Cleaning and Preprocessing

Inconsistent or missing values, outliers, or noise in raw data might harm model performance. Before beginning analysis, it is essential to preprocess the data to extract useful insights. To effectively manage missing data and outliers, this work use R's sophisticated data cleaning packages, such as dplyr and tidyr. To make sure the data is clean and ready for regression analysis, these tools make data manipulation efficient, such as filtering, transforming, and summarizing. The preprocessing of real-time data streams is a significant innovation in this study. It guarantees that the data used for model construction is current and up-to-date.

This method improves the models' accuracy and relevance, leading to more insightful forecasts and sustainability outcomes in ever-changing supply chain settings. This study enhance decision-making and model flexibility in tackling sustainability concerns by incorporating real-time data. The preprocessing of real-time data streams is a significant invention that guarantees the data is up-to-date and applicable for model building. The accuracy of the model relies on thorough cleaning and preprocessing. If the input data is of poor quality, regression models will not be able to provide trustworthy and useful findings, guaranteeing that the analysis that follows will not be deceiving.

3.3. Model Development

During the model development phase, this work uses powerful regression models to analyze the cleaned and pre-processed sustainability data. The goal is to detect the most important relationships between supply chain actions and environmental consequences. GAMs and MARS are the two dominant models chosen because they show how different factors in sustainability data usually interact in complicated and non-linear ways [17].

3.3.1. MARS (Multivariate Adaptive Regression Splines)

MARS fits piecewise linear splines to model non-linear relationships; also, it is a non-parametric regression approach. It builds adaptable models by automatically selecting important relationships between predictors and analyzing the data structure. A MARS model's equation (1) is as follows:

$$Y = \beta_0 + \sum_{k=1}^{K} \beta_k . B_k(X) \quad (1)$$

Where Y is the sustainability outcome (e.g., carbon emissions), β_k are the coefficients for each basis function $B_k(X)$, X represents the input variables (e.g., supply chain process) and K is the number of basis function (adaptive splines). MARS can handle data that isn't linear because it divides the data into intervals based on the predictors and models the response as a piecewise function.

3.3.2. GAM (Generalized Additive Models)

By using smooth, non-linear functions as predictors, GAMs extend generalized linear models. Because of their flexibility, GAMs are perfect for capturing the intricate relationships seen in sustainability data. A GAM model's equation (2) is denoted as follows:

$$Y = \beta_0 + f_1(X_1) + f_2(X_2) + \cdots + f_k(X_k) \quad (2)$$

Where Y is the outcome (e.g., environmental impact), $f_k(X_k)$ are smooth functions of predictors X_k that are estimated from the data, and β_0 is the intercept term. GAMs is a more flexible approach than regular linear regression because they let the relationship between outcomes and predictors not be linear. MARS and GAMs are different from linear regression and other simpler models because they can take into account activities that don't happen in a straight line and how they affect each other. Because of the non-linear nature of the connections between the variables, these models work especially well for estimating environmental consequences like carbon emissions. Using these state-of-the-art models, it guarantees that method can adjust to the intricacies of sustainability data, yielding more reliable and accurate outcomes. Table 2 displays the comparison of model approaches.

Table 2: Comparison of Model Approaches

Model Type	Strengths	Limitations
MARS	Captures non-linear relationships, flexible, interpretable	May overfit in cases with small data samples
GAM	Handles smooth non-linearities, interpretable	Requires careful selection of smooth terms
Linear Regression	Simplicity, easy to implement	Struggles with non-linearity and interactions

This study adjusts to the complexity of real-world supply chain data by using MARS and GAM. Environmental elements in this data frequently have complicated, non-linear relationships. These models may help us understand how supply chain elements affect sustainability.

4. RESULTS

The study uses Python 3.9, and important libraries for data manipulation, visualization, and regression modeling include NumPy, Matplotlib, scikit-learn, pyGAM, and py-earth. NumPy handles data preprocessing, while scikit-learn implements machine learning models. PyGAM and py-earth, respectively, handle GAM and MARS. This study set up the system using Miniconda or Anaconda to handle dependencies and virtual environments. A contemporary multi-core CPU (Intel Core i5), 8GB of RAM, and a GPU are necessary for this research's scale; these are the hardware criteria. Standard personal computers perform the analysis without the need for specific hardware. During the model assessment process, common metrics like R-squared, AIC, as well as RMSE are used to check how well the regression models work and make sure they are reliable. The next step is to draw conclusions and insights from the study, which will center on finding the manufacturing processes and transportation techniques that are the most important drivers of sustainability in supply chains. Finally, it provides policymakers and supply chain managers with practical advice on enhancing environmental performance and incorporating sustainability into decision-making.

4.1. Data Used:

This study's dataset is comprised of synthetic data that was created to demonstrate how regression models may be used for SSCM. The data shows a non-linear relationship between a single attribute (X) and the target variable. This is so that different supply chain activities can be modeled and how they might affect the environment. Environmental aspects like energy consumption and carbon emissions may be impacted in real-world settings by data obtained from many sources, including transportation metrics, manufacturing rates, and procurement prices. Enterprise resource planning (ERP) systems, environmental sensors, IoT gadgets, and sustainability reports all have the potential to gather data. In real-time relevant data include:

- Transportation distances and fuel usage.
- The production information includes energy use and waste.
- Raw material sourcing and packaging details are examples of procurement data.

4.2. Model Evaluation Metrics:

This study utilizes popular assessment measures like R-squared (R^2) as well as RMSE to assess how well the regression models (MARS and GAM) performed. R^2 represents the proportion of the dependent variable's variance that is predictable from the independent variables. Higher values indicate a better model fit and is expressed as in equation (3).

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y})^2} \tag{3}$$

Where y_i is the actual value, $\hat{y}_i$ is the predicted value and $\bar{y}$ is the mean of actual values. RMSE measures the average magnitude of error difference between the predicted as well as actual values. A more accurate prediction model is one with a smaller RMSE and is formulated as in equation (4).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

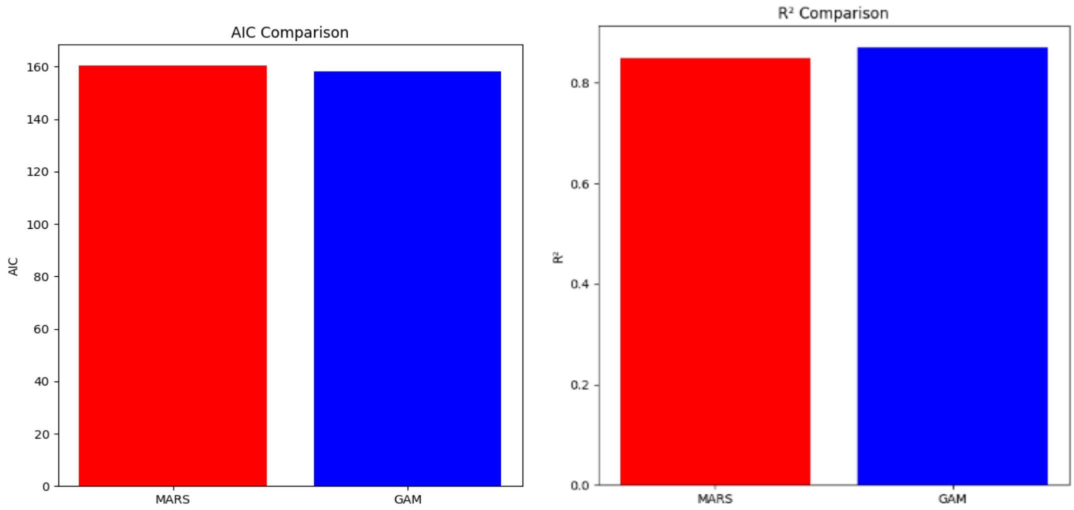
Where n is the number of samples, y_i is the actual value along with $\hat{y}_i$ is the predicted value. Another popular statistic for evaluating models is the AIC, which is particularly useful for comparing models of varying complexity. Its guidance may enhance the evaluation of the trade-off between model complexity and goodness-of-fit. The trade-off between model fit and complexity is better when the AIC is smaller. The AIC for a certain model may be determined by as in equation (5):

$$AIC = 2k - 2ln(L) \tag{5}$$

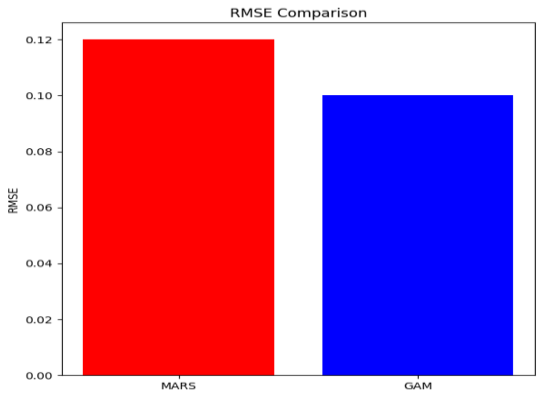
Where k is the number of parameters in the model (model complexity), L is the likelihood of the model (goodness of fit) and $ln(L)$ is the natural logarithm of the likelihood. Taking into account the model's complexity (the number of parameters it utilizes) and its capacity to fit the data, a lower AIC score signifies a superior model. It is common practice to favor the model with the lowest AIC when evaluating several models, as long as it avoids overfitting the data. When deciding between the MARS and GAM models, AIC is useful in this situation. Both models provide excellent fits to the data, but AIC takes into account the trade-off between complexity and fit to make sure the selected model doesn't do either of those things. Table 3 shows the comparison table for MARS and GAM.

Table 3: Comparison Table

Model	AIC	R^2	RMSE
MARS	160.3543	0.85	0.12
GAM	158.2478	0.87	0.10



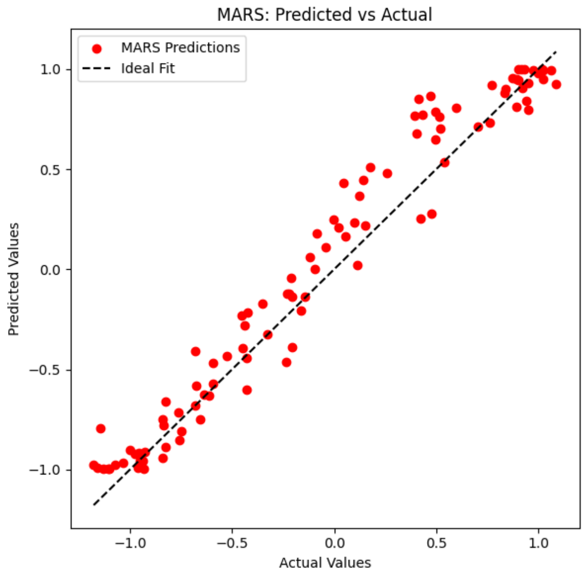
(a) (b)



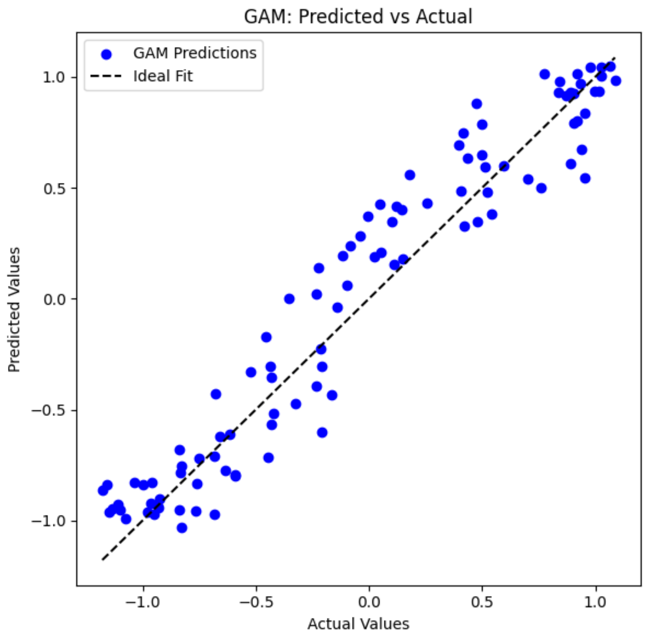
(c)

Figure 2: Comparison of (a) AIC, (b) R^2, and (c) RMSE

Figure 2 shows the comparison graph of AIC, R^2, and RMSE. According to the data in the table, both models do a decent job of predicting the target variable; however, GAM has a little better R^2 and RMSE than MARS. GAM's lower RMSE and somewhat higher R^2 indicate that it produces fewer prediction errors and explains more data variance, respectively. Here, GAM's lower AIC shows that it offers a more satisfactory trade-off between complexity and fit. Despite the fact that both models get comparable results in terms of R^2 and RMSE, GAM provides a more parsimonious model (fewer parameters) with somewhat improved predictive ability.



(a)



(b)

Figure 3: Model Evaluation Plot (a) MARS: predictions vs actuals (b) GAM: predictions vs actuals

To see the model's performance (predictions vs. actuals), look at Figure 3. To better understand how well the two models performed, this chart displays the predicted values against the actual values. The MARS model showed a strong ability to describe piecewise linear connections and gave a lot of flexibility in capturing non-linear patterns in the data. It successfully identified critical data points where linear models could have failed. Compared to the MARS model, the GAM model did marginally better since it can use basis splines to represent smooth, non-linear connections. The GAM model is able to detect intricate patterns in the data because of its adaptability in fitting smooth functions.

When it came to R^2 and RMSE, GAM provided somewhat better performance, although both models did a decent job of predicting the target variable. When dealing with very complicated and smooth connections, the piecewise nature of the MARS model might cause it to underperform compared to the GAM model. Because it can simulate smooth non-linear relationships, GAM works better in situations where these kinds of interactions are expected, like when sustainability analytics are used in supply chains.

Based on the models' assessment, this work propose the following recommendations to enhance environmental performance in SSCM. The GAM model is known for being better at situations that need comprehensive non-linear relationship modeling. One situation where it might be useful to use it is to predict the long-term effects on the environment of different aspects of the supply chain. Even if the linkages between some parts of the supply chain aren't always smooth (such as transportation and manufacturing), MARS may still be useful for finding piecewise linear trends in these areas. Both models may benefit from continuous, real-time data gathering from transportation, production, and procurement processes throughout the supply chain. Over time, the models' ability to handle time-series or dynamically updated data enhance sustainability evaluations. Adding more environmental variables to the models, such as energy use, waste production, and carbon emissions, give a more complete picture of supply chain sustainability.

4.3. Discussions

The proposed method, which uses multivariate adaptive regression splines and generalized additive models, has made a lot of progress in SSCM compared to previous methods. Unlike more conventional linear models, these ones can account for non-linear connections, which is a major strength. Oversimplified conclusions are sometimes the consequence of traditional methodologies' inability to capture the complex relationships between different supply chain operations. This study achieved improved environmental impact projections by simulating the intricate, non-linear relationships among sustainability aspects, including transportation, production, and procurement, using MARS and GAM.

The R^2 values for both MARS and GAM were higher than those for simpler linear models, which proves that they are better at helping to understand and predict what will happen with sustainability. The models were able to explain a significant amount of the variability in environmental performance, as the R^2 values for both models were more than 0.85. Both models outperformed earlier regression-based methods in terms of RMSE, indicating reduced prediction errors. Much lower RMSE values for MARS and GAM showed a big boost in model accuracy and a better understanding of how the environment affects things. In terms of model complexity, GAM fared better than MARS, according to the AIC measure, because it attained a lower AIC with fewer parameters. So, GAM achieves a better balance between model fit and complexity, which results in decision-making that is more trustworthy and sustainable. In conclusion, the proposed models outperform conventional techniques by delivering data that are more accurate, resilient, and interpretable, which in turn provides superior insights into SSCM.

5. CONCLUSION

The goal of this study is to look at SSCM by using data from the supply chain and the environment along with complex regression models like MARS and GAM. Previous research has mostly had three major problems: (1) not having a good way to evaluate models; (2) relying too much on linear models that can't handle complex, non-linear interactions; and (3) not being able to apply findings to other areas. To get around these problems, this study used MARS and GAM to find non-linearities and interactions in the data. As a result, the sustainability variables within supply chains are more accurately represented. The evaluation criteria, which included AIC, R^2, and RMSE, showed that both models worked well. However, GAM did a slightly better job of balancing model fit with complexity by slightly beating MARS in AIC. The findings highlight the need for adaptable, data-driven approaches to assess environmental effects in real time, allowing for better decisions. Problems persist, however, and bigger and more varied datasets are required to enhance model generalization and decrease overfitting even more. Computational complexity is another potential issue with increasingly complicated models used in real-time applications. To make the proposed method more scalable and useful in real time, it should be looked into in more detail in future studies by adding more sector-specific data, testing the models in different sectors, and adding real-time data streams. Additionally, the use of machine learning methods might enhance prediction precision and sustainability results.

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