Journal of Science and Social Research ISSN 2615 – 4307 (Print)
Oct 2026, IX (5): 8951 – 8962 ISSN 2615 – 3262 (Online)
Available online at http://jurnal.goretanpena.com/index.php/JSSR

A REVIEW OF CARBON FOOTPRINT PREDICTION MODELS: METHODS, ADVANCES, AND FUTURE DIRECTIONS

Roni Yunis[1], Irpan Adiputra Pardosi[2]
Universitas Mikroskil, Medan
e-mail: [1]roni@mikroskil.ac.id, [2]irpan@mikroskil.ac.id

Abstract: *This study provides a systematic review of carbon footprint prediction models, examining methodological developments, existing challenges, and future research directions. As a crucial tool for climate change mitigation and sustainable environmental management, carbon emission prediction has attracted growing academic attention. A comprehensive literature search was conducted in leading databases, including Scopus, Web of Science, and Google Scholar, focusing on peer-reviewed articles from 2018 to 2024. The review covers a wide range of modeling approaches, such as process-based, input-output, hybrid, grey system, and AI-based models. Although significant progress has been made, issues concerning data quality, model complexity, scalability, and transparency persist. The study also highlights emerging technologies, including AI, big data, IoT, and blockchain, which enhance prediction accuracy and adaptability. Furthermore, it underscores the importance of standardized methods, Explainable AI (XAI), and flexible modeling frameworks for future research. Overall, this review offers valuable insights to inform future studies and policymaking in carbon footprint prediction and climate action.*

Keyword: *carbon footprint prediction, method, machine learning, sustainability, future directions*

INTRODUCTION

In recent years, there has been increasing attention to developing complex models that estimate carbon footprints across various sectors. These models are essential for understanding and mitigating the impact of human activities on the environment. This aligns with the ontological statement that the use of machine learning, deep learning, and time series analysis (Yunis et al., 2024) to produce more accurate predictions efficiently. Adopting these new methodologies allows us to understand the emission fluctuations from human activities and develop more effective strategies for mitigating adverse environmental impacts.

Modelling across various industries and sectors has advanced considerably. For example, carbon footprint predictions have been applied in the thermal power generation industry in Zhejiang Province, China (Zhang, 2023), the energy sector in West India (Kaur, 2024), clinical laboratories (Ni et al., 2018), and urban buildings in Malaysia (Gardezi & Shafiq, 2019). These models have been helpful for estimating current carbon footprints and play a vital role in formulating future carbon reduction strategies.

Currently, more comprehensive techniques based on machine learning and artificial intelligence have revolutionized carbon footprint predictions. Several studies have employed neural networks (Acheampong & Boateng, 2019), random forest (Nguyen et al., 2021), and gradient-boosting regression (Cai et al., 2020) to enhance accuracy. These approaches facilitate the handling of complex datasets and generally improve the reliability of carbon footprint forecasting. Additionally, the combination of Data Envelopment Analysis with multivariate statistics allows for in-depth analysis of energy optimization strategies and carbon footprint reduction.

The integration of these

methodologies helps researchers identify inefficiencies in energy usage and design interventions to minimize carbon emissions effectively. Moreover, innovations such as grey Verhulst (Tong et al., 2021), grey Riccati (Gao et al., 2021), and grey Bernoulli (Wang & Wang, 2023) provide specific methods for forecasting carbon footprints. By applying grey system theory, these models address uncertainties and data fluctuations, enhancing prediction resilience.

Despite significant advancements in carbon footprint prediction models, there remains a lack of universally reliable, scalable, and adaptable models. These models must account for diverse industries and effectively manage data uncertainty. However, the absence of such comprehensive models limits the effectiveness of carbon reduction strategies. Therefore, further refinement is crucial to enhance their role in mitigating environmental impacts. Addressing this issue is vital for the success of future climate change initiatives, despite the challenges that persist.

To address the complexity and evolving nature of carbon footprint prediction models, this study seeks to explore several key research questions (RQs) that are critical for advancing the field.

RQ1: How can AI and big data integration improve the accuracy of carbon footprint predictions, and what challenges hinder the development of transparent and reliable models? This question is essential in understanding the role of emerging technologies in enhancing predictive capabilities while also addressing concerns related to model interpretability and data quality.

RQ2: How can hybrid models, combining process-based and input-output approaches, provide comprehensive insights for mitigating carbon footprints across sectors? This question aims to examine the potential of integrated modeling approaches to deliver more holistic and actionable carbon footprint assessments applicable to various industries and contexts.

RQ3: What are the key research gaps in carbon footprint modeling across sectors, and how can interdisciplinary approaches address these challenges? This question highlights the need to identify unresolved issues in the current modeling landscape and emphasizes the importance of cross-disciplinary collaboration to develop more robust, adaptable, and policy-relevant models. By addressing these research questions, this review aims to synthesize current advancements, challenges, and future directions in carbon footprint modeling, providing valuable insights for researchers, practitioners, and policymakers engaged in climate change mitigation efforts.

METHODOLOGY

Figure 1 outlines the methodology used for the review process.

Literature Search Strategy

A systematic literature search was conducted using databases such as Scopus, Web of Science, and Google Scholar, along with journals like Environmental Science and Pollution Research, Journal of Cleaner Production, and International Journal of Environmental Research and Public Health. Keywords included "carbon footprint," "greenhouse gas emissions," "CO_2 prediction," "machine learning," and "time series."

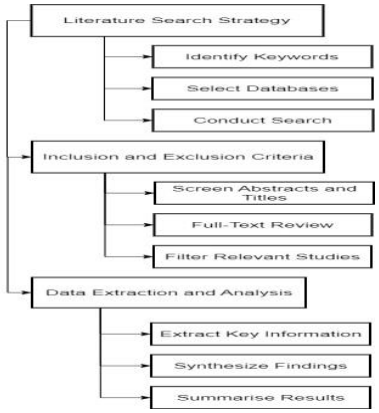


Figure 1 Literature Review Methodology

Journal of Science and Social Research ISSN 2615 – 4307 (Print)
Oct 2026, IX (5): 8151 – 8162 ISSN 2615 – 3262 (Online)
Available online at http://jurnal.goretanpena.com/index.php/JSSR

Inclusion and Exclusion Criteria

Inclusion criteria required studies to (1) explicitly focus on carbon footprint prediction models, (2) utilize data-driven modeling techniques, (3) be published in reputable journals, and (4) be peer-reviewed articles published between 2019 and 2024. The exclusion criteria include: (1) studies unrelated to carbon emission prediction, (2) studies lacking sufficient methodological details, and (3) non-peer-reviewed or unverified articles.

Data Extraction and Analysis

The researchers conducted a systematic data extraction and analysis to examine recent developments in carbon emission prediction. This process included collecting information on various prediction models, greenhouse gas emissions, and supporting technological innovations. The analysis involved comparative assessments of models, visualization methods, and bibliometric techniques to uncover emerging trends and patterns in carbon emission prediction research.

RESULT AND DISCUSSION

Data Review and Keywords

Figure 2 presents a word cloud illustrating the most frequent terms in the abstracts of the reviewed studies. The results indicate that most studies utilized diverse models and analytical techniques to predict and reduce carbon emissions. This review primarily focuses on the models applied for carbon emission analysis.

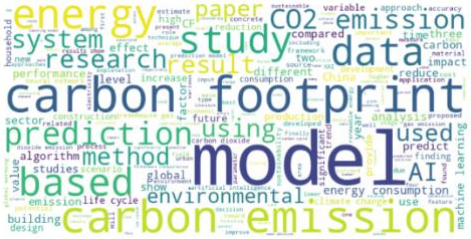


Figure 2 Carbon Emission Word Cloud

Figure 3 shows the number of studies selected for this review, totaling 188 journal articles identified through the defined keywords. The highest number of publications on carbon emission models appeared in 2021 (24.3%), followed by 2023 (22.2%).

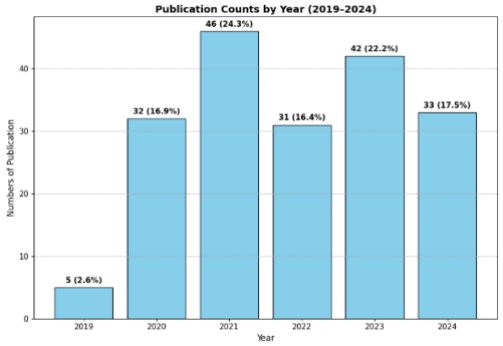


Figure 3 Number of Publications per Year

Numerous publications address environmental and sustainability issues, with carbon emission prediction emerging as the most frequently discussed topic (Table 1). This highlights the growing research interest in carbon emission prediction across a wide range of journals. The query used for the research in the Scopus database is as follows:

(TITLE-ABS-KEY ("carbon emission prediction") AND PUBYEAR > 2018 AND PUBYEAR < 2025 AND SRCTITLE ("Name Journal"))

Table 1 Carbon Emission Prediction Journals

Publisher	Journals
Elsevier Ltd	Journal of Cleaner Production
	Renewable and Sustainable Energy Reviews
	Energy
Elsevier B.V.	Science of the Total Environment
	Energy Economics
	Neurocomputing
Springer Nature	Environmental Science and Pollution Research
IEEE	IEEE Access
Springer Berlin Heidelberg	International Journal of Environmental Science and Technology

Journal of Science and Social Research ISSN 2615 – 4307 (Print)
Oct 2026, IX (5): 8151 – 8162 ISSN 2615 – 3262 (Online)
Available online at http://jurnal.goretanpena.com/index.php/JSSR

Historical Review of Carbon Emission Models

Early carbon emission models primarily relied on basic calculations and simple emission factors to estimate direct and indirect greenhouse gas emissions. Developed in response to increasing environmental awareness, these models laid the foundation for the advancement of more sophisticated modeling approaches (Akyol & Uçar, 2021)(Lim et al., 2023). As technology advanced, carbon emission models evolved by integrating new algorithms, data-driven approaches, machine learning models, and convolutional neural networks. Incorporating these approaches enhanced the accuracy and resilience of the models (Płoszaj-Mazurek et al., 2020)(Li & Sun, 2021)(Bussaban et al., 2023)(Thilakarathna et al., 2020)(Geevaretnam et al., 2022).

The comparison between early and modern models shows a significant increase in complexity and accuracy. Modern models provide more detailed insights to support better environmental decision-making and policies (Hans et al., 2023)(Norton et al., 2023). Overall, the development of carbon emission models reflects a substantial transformation driven by technological innovations and a deeper scientific understanding of climate change.

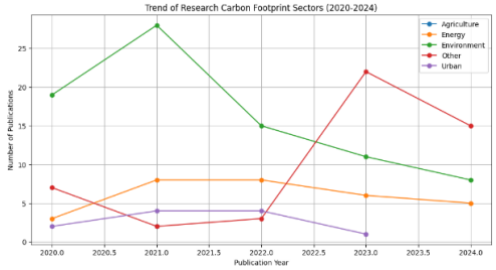


Figure 4 Carbon Emission Sector Trends

The sector analysis of carbon emissions in Figure 4 indicates that most of the selected studies focused on the environmental sector, representing 47.5% of the sample.

Categories of Carbon Emission Models

The following section describes several categories of carbon emission models.

1. *Process-Based Models:* Process-based models estimate carbon emissions by examining specific activities or processes that generate greenhouse gas emissions. With the integration of real-time data monitoring and advanced simulation techniques, these models have become more accurate. Machine learning and parametric design are also applied, particularly in building sector models, to optimize carbon emissions and ensure precise calculations across the product lifecycle (Płoszaj-Mazurek et al., 2020). Similarly, they highlight carbon emissions in industries and stress the importance of comprehensive governance and industry restructuring to achieve low-carbon transformation (Zhang, 2023). Integrating real-time data monitoring enhances these models' predictive capabilities (Lim et al., 2023). CO_2 emissions using machine learning also illustrate how these models can forecast future emissions based on historical data (Meng & Noman, 2022). The evolution of process-based models, characterized by the integration of real-time data and the latest simulation techniques, provides valuable insights into carbon emissions at various stages. These models improve the accuracy of emission calculations and facilitate the development of strategies for carbon emission reduction.
2. *Input – Output Models:* Input-output models play a crucial role in analyzing intersectoral linkages, particularly in estimating carbon emissions. For example, this model has been applied to a city-centric global multiregional input-output model, allowing for a more in-depth evaluation of urban carbon emissions

(Han et al., 2022). The use of big data analytics in input-output models enables more dynamic emission assessments, especially in the context of rapidly changing economic conditions and consumption patterns. Additionally, the use of open data and machine learning to refine predictions aligns with trends about utilizing better computational techniques to enhance the accuracy of carbon emission evaluations (Li & Sun, 2021). Thus, advances in input-output models are marked by the integration of big data, machine learning, and more accurate emission factors, significantly improving the accuracy of carbon emission evaluations.

3. *Hybrid Models:* Hybrid models combine process-based and input-output approaches to provide a comprehensive view of carbon emissions. These models leverage the strengths of both methods to improve accuracy and capture emission details across various sectors (Janković et al., 2021)(Wen & Yuan, 2020). Hybrid models combine various modeling approaches to provide a comprehensive understanding of carbon emissions and potential mitigation strategies. Recent innovations, such as the incorporation of artificial intelligence, convolutional neural networks (CNN), and parametric design, have enhanced the predictive power and scalability of these models, making them essential tools in carbon emission management (Meng & Noman, 2022)(Sun & Ren, 2021).
4. *Recent Models:* New approaches, such as AI-based methods for carbon emissions modelling, are revolutionizing the field by enhancing prediction accuracy and efficiency. The use of machine learning to predict CO2 emissions highlights AI's role in guiding decision-making processes toward achieving net-zero carbon emissions (Bolón-Canedo et al., 2024). These innovative approaches leverage new technologies to handle complex datasets and improve the predictive capabilities of carbon emissions models.

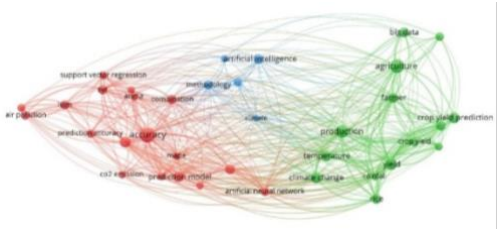


Figure 5 Network Visualization

Figure 5 exhibits the Network Visualization generated from VOSviewer, indicating that research on prediction in the field of climate change is structured around three interconnected clusters, namely methodological approaches emphasizing prediction models and accuracy metrics (red cluster), conceptual and technological foundations of artificial intelligence and methodological development (blue cluster), and application-oriented studies focusing on climate-related variables such as temperature and rainfall (green cluster), thereby highlighting the integration of machine learning techniques with environmental data to enhance predictive accuracy and practical relevance.

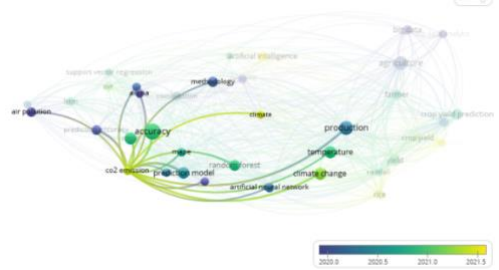


Figure 6 Co-Occurrence Visualization Based on Keywords

Figure 6 mapping shows that research on climate change prediction centers on key themes such as climate modeling, machine learning, CO_2 emissions, and remote sensing. A notable finding is the strong interconnection between machine learning and climate

modeling, highlighting their increasing integration over time. The color transition from blue to yellow indicates that topics like machine learning and deep learning have gained significant momentum in recent years, signaling a shift toward data-driven methodologies in climate forecasting. This evolution is consistent with the advancement of hybrid models designed to improve computational efficiency, minimize uncertainty, and enhance the accuracy of predictions related to temperature, precipitation, and extreme weather phenomena. In addition, the central positioning of CO_2 emissions emphasizes its importance as a critical forcing factor in climate projections, frequently employed in emission scenarios to model potential future outcomes under various mitigation strategies.

Recent Innovations in Carbon Emissions Models

Recent innovations in carbon emissions models are driven by the application of the following latest technologies and techniques:

1. *AI and Machine Learning in Carbon Emissions Models:* AI and machine learning have greatly advanced carbon emissions modeling, leading to more accurate predictions and analyses. As shown in Figure 7, there is a clear upward trend in the use of machine learning algorithms for carbon emissions prediction. This growth is likely due to machine learning and deep learning's capacity to efficiently process large datasets and identify patterns that traditional models may miss. Moreover, machine learning has demonstrated high accuracy in carbon emissions prediction (Meng & Noman, 2022)(Nguyen et al., 2021). Additionally, AI advances for carbon emissions modelling have improved predictive power overall, supporting better decision-making (C. Y. Chen et al., 2021)(Ayman Naji Khallaf, 2024).

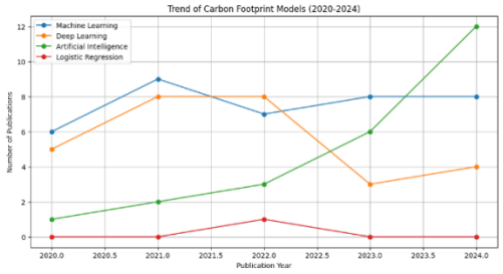


Figure 7 Trends in Carbon Emission Models

2. *Big Data and IoT:* Big data analytics and IoT have revolutionized carbon emissions modelling by enabling real-time processing of large datasets. The model discussed in (Luo et al., 2024) leverages open data and machine learning to predict CO_2 emissions, demonstrating the strength of data-driven approaches in understanding and managing carbon emissions. Moreover, integrating IoT devices for data collection and analysis further enhances the level of detail and accuracy in carbon emissions assessments (Pirson & Bol, 2021)(Fang et al., 2024).
3. *Geospatial and Remote Sensing Techniques:* Advancements in geospatial analysis and remote sensing have opened new opportunities for assessing carbon emissions at a spatial scale. Research (Li & Sun, 2021) showed that easily accessible statistical records and geospatial data in urban areas can accurately predict CO_2 emissions at the city level with the help of machine learning or deep learning algorithms.
4. *Challenges and Opportunities:* The use of technology in carbon emissions modeling presents both challenges and opportunities. One key challenge is the need for expertise in data science and environmental science to manage the complexity of these models. Moreover, without ensuring accuracy, reliability, and data security, integrating AI-driven big data into carbon emissions modeling

becomes even more difficult. The need to maintain and update technological infrastructure further adds to the complexity of implementation.

Despite persistent challenges, carbon footprint modelling presents significant opportunities for innovation and progress. The integration of AI, machine learning, and big data enables the development of sophisticated models that capture complex interrelationships among variables, thereby improving predictive accuracy. Equally important, real-time monitoring supported by IoT facilitates proactive emission reduction and adaptive management. Taken together, these advances open new pathways for accurate forecasting, continuous monitoring, and effective climate change mitigation.

Research Gaps in Carbon Footprint Prediction Across Sectors

Table 2 shows recent studies discussing carbon emissions prediction.

Table 2 Summary of Research in Carbon Footprint Prediction Models

Ref.	Models	Metric	Sector	Research Findings
(Zhang, 2023)	GBDT Meta Learner	R2: 0.9944 MAPE: 0.0047	Energy	Time series data link economic growth to carbon emissions, with power generation as a major contributor.
(Akyol & Uçar, 2021)	SMOreg	MSE: 79.0241 MAPE: 1.888	Energy	
(Lim et al., 2023)	MLP	MSE: 5304890 MAPE: 1.2314	Energy	
(Płoszaj-Mazurek et al., 2020)	CNN	EE: 1.6%	Environment	Enhanced process representation, machine learning, deep learning like TCN, and multivariate prediction improve CO_2 accuracy and capture carbon sensitivity.
(Geevaretnam et al., 2022)	SVM	MAE: 65.7254 RSME: 112.2196 MAPE: 0.2279%	Environment	
(Norton et al., 2023)	DALEC-Knorr	R: 0.78 RMSE: 2.5 $gCm^{-2}d^{-1}$	Environment	
(Meng & Noman, 2022)	SARIMAX	MAPE: 32%, 28%, 19%, 9%	Environment	
(Chiu et al., 2020)	MGPM	MAPE: 1.87	Environment	
(J. Chen et al., 2024)	TCN	MAE: 2.43 RSME: 3.31 MAPE: 8.8%	Environment	
(C. Y. Chen et al., 2021)	LSTM	RMSE: 0.1633 MAPE: 16.35% R2: 0.963	Environment	
(Hans et al., 2023)	SVR	MAE: 129.41 RSME: 158.03 R2: 0.98 MAPE: 15.83	Education	Carbon emissions analysis of educational institution operations.
(Hidayat, 2024)	LR	R2: 0.775	Education	
(Gao et al.,	FGRM	MAPE: 0.80%	Urban	Bernoulli, Riccati,

2021)		R2: 0.8284		Grey Rolling, and geospatial models surpass traditional methods in predicting CO_2 emissions.
(Wang & Wang, 2023)	NFOGBM	MAPE: 1.25% MRSPE: 0.88% CMRPE: 0.95%	Urban	
(Li & Sun, 2021)	XGBoost	R2: 0.98 RSME: 0.8% MAE: 0.7%	Urban	
(W. Zhou et al., 2021)	NGRPM	MAE: 144.14 RSME: 169.48 MAPE: 1.69%	Urban	
(Marçal et al., 2021)	Random Forest	MAE: 6.87 RMSE: 8.56 R2: 0.91	Agroforestry	Random Forest models show strong potential for predicting soil carbon stocks.

Despite technological advancements, carbon emissions modeling still faces significant gaps. Limited cross-sectoral and regional studies hinder a comprehensive understanding of carbon impacts. Further research is needed to enhance the scalability of AI models and to develop Explainable AI (XAI) for transparent and adaptive carbon emissions predictions.

Challenges and Iterations in Carbon Emissions Modelling

Carbon emissions modeling encompasses complex environmental, economic, and social dimensions. Despite technological progress, issues of data quality, uncertainty, and model stability continue to hinder prediction accuracy. This section outlines key challenges in model development and highlights the need for continuous research to improve predictive performance.

1. *Data Quality and Availability:* One of the primary challenges in carbon emissions modelling is the lack of quality, availability, and reliability of data. Complexities arise from emission data that do not meet statistical assumptions, leading to uncertainties in modelling outcomes (Chiu et al., 2020)(Akyol & Uçar, 2021). Meanwhile, data reliability heavily depends on the accuracy and completeness of the datasets used, presenting a significant challenge in ensuring the accuracy of carbon emissions predictions.
2. *Model Complexity and Uncertainty:* Another significant challenge is related to the complexity and uncertainty of various carbon emissions models. The uncertainty in predicting carbon emissions stems from the dynamic nature of the carbon cycle and the limitations of current modelling approaches (Spring et al., 2021). High ecosystem complexity, coupled with a lack of comprehensive data for parameterization (Wilkes et al., 2020)(C. Zhou et al., 2024) hinders the development of generic and accurate models for carbon emissions prediction. This challenge underscores the importance of developing better methodologies to address uncertainty effectively.
3. *Scalability and Adaptability:* Scalability and adaptability are also challenges that require attention in carbon emissions modelling. Carbon emissions predictions highlight the need for models that can be accelerated for broader environmental assessments (Bolón-Canedo et al., 2024)(Mosso et al., 2024). Ensuring that models can adapt to various sectors, regions, and scenarios is crucial for enhancing

their usability and effectiveness in supporting decision-making processes related to carbon management and mitigation strategies.

Future Directions in Carbon Emissions Modelling

The review of previous studies highlights several recommendations to address existing gaps and outlines potential directions for future research:

1. *Establishing Standard Methods:* Developing standard methods for data collection, processing, and analysis to optimize accuracy in carbon emissions calculations.
2. *Interdisciplinary Research:* Initiating interdisciplinary research that connects environmental impacts with carbon emissions and explores synergies for sustainability initiatives.
3. *Decentralizing Carbon Emissions Modelling:* Testing the scalability of AI models across various sectors and regions to ensure their applicability can be adapted to different contexts.
4. *Developing XAI Models for Dynamic Carbon Emissions Prediction:* Advancing AI model interpretability and transparency to ensure that users and policymakers can understand the rationale behind predictions. Emphasis should be placed on explanation and adaptability to dynamic data changes, rather than focusing solely on accuracy or cross-sector applications.
5. *Developing New Technologies:* Utilizing other innovative technologies such as blockchain and remote sensing to expand timely monitoring and tracking of carbon emissions.

Future research can accelerate advancements in carbon emissions modelling by promoting sustainability and supporting international efforts to combat climate change effectively, as agreed upon in the Paris Agreement.

CONCLUSION

This systematic review of carbon emissions models highlights several key findings. First, the integration of AI and machine learning has greatly enhanced prediction accuracy. Nevertheless, data quality and availability remain major challenges that impact the reliability of model outcomes. The complexity and inherent uncertainties of existing models also emphasize the need for improved methodologies to address these issues. Strengthening collaboration among academia, industry, and government is crucial to advancing carbon emissions models and supporting sustainability efforts. In addition, this review highlights the importance of hybrid models, which combine process-based and input-output approaches, in providing comprehensive insights for carbon emissions mitigation across sectors.

Advancements in carbon emissions modeling hold significant implications for global climate change mitigation. An interdisciplinary approach that integrates environmental science, economics, and data science can lead to the development of more robust and accurate models to support informed decision-making. Incorporating emerging technologies such as Explainable AI (XAI), quantum computing, and blockchain offers the potential to enhance model accuracy, transparency, and interpretability. Supporting this research direction and continuously improving carbon emissions models can greatly advance sustainable practices and environmental awareness. Ultimately, ongoing innovation and a commitment to sustainability will enable carbon emissions modeling to play a leading role in addressing climate change and securing a healthier future for coming generations.

ACKNOWLEDGMENT

Thanks to Universitas Mikroskil for the generous funding provided through.

This contribution has played a crucial role in the success of the research, and we are deeply grateful for the university's commitment to advancing research and academic excellence.

REFERENCES

Acheampong, A. O., & Boateng, E. B. (2019). Modelling carbon emission intensity: Application of artificial neural network. *Journal of Cleaner Production*, *225*, 833–856. https://doi.org/10.1016/j.jclepro.2019.03.352

Akyol, M., & Uçar, E. (2021). Carbon footprint forecasting using time series data mining methods: the case of Turkey. *Environmental Science and Pollution Research*, *28*(29), 38552–38562. https://doi.org/10.1007/s11356-021-13431-6

Ayman Naji Khallaf. (2024). Using Ai to Help Reduce the Effect of Global Warming. *Power System Technology*, *48*(1), 1927–1947. https://doi.org/10.52783/pst.464

Bolón-Canedo, V., Morán-Fernández, L., Cancela, B., & Alonso-Betanzos, A. (2024). A review of green artificial intelligence: Towards a more sustainable future. *Neurocomputing*, *599*(June), 128096. https://doi.org/10.1016/j.neucom.2024.128096

Bussaban, K., Kularbphettong, K., & Boonseng, C. (2023). *Prediction of Co 2 Emissions Using Machine Learning*. 7250.

Cai, J., Xu, K., Zhu, Y., Hu, F., & Li, L. (2020). Prediction and analysis of net ecosystem carbon exchange based on gradient boosting regression and random forest. *Applied Energy*, *262*(November 2019), 114566. https://doi.org/10.1016/j.apenergy.2020.114566

Chen, C. Y., Chai, K. K., & Lau, E. (2021). AI-Assisted approach for building energy and carbon footprint modeling. *Energy and AI*, *5*(May), 100091. https://doi.org/10.1016/j.egyai.2021.100091

Chen, J., Cui, Y., Zhang, X., Yang, J., & Zhou, M. (2024). Temporal Convolutional Network for Carbon Tax Projection: A Data-Driven Approach. *Applied Sciences (Switzerland)*, *14*(20). https://doi.org/10.3390/app14209213

Chiu, Y. J., Hu, Y. C., Jiang, P., Xie, J., & Ken, Y. W. (2020). A Multivariate Grey Prediction Model Using Neural Networks with Application to Carbon Dioxide Emissions Forecasting. *Mathematical Problems in Engineering*, *2020*. https://doi.org/10.1155/2020/8829948

Fang, Z., Xu, X., Bilal, M., & Jolfaei, A. (2024). Renewable prediction-driven service offloading for IoT-enabled energy systems with edge computing. *Wireless Networks*, *30*(5), 3721–3733. https://doi.org/10.1007/s11276-021-02740-w

Gao, M., Yang, H., Xiao, Q., & Goh, M. (2021). A novel fractional grey Riccati model for carbon emission prediction. *Journal of Cleaner Production*, *282*, 124471. https://doi.org/10.1016/j.jclepro.2020.124471

Gardezi, S. S. S., & Shafiq, N. (2019). Operational carbon footprint prediction model for conventional tropical housing: a Malaysian prospective. *International Journal of Environmental Science and Technology*, *16*(12), 7817–7826. https://doi.org/10.1007/s13762-019-02371-x

Geevaretnam, J. L., Megat Mohd. Zainuddin, N., Kamaruddin, N., Rusli, H., Maarop, N., & Wan Hassan, W. A. (2022). Predicting the Carbon Dioxide Emissions Using Machine Learning. *International Journal of Innovative Computing*, *12*(2), 17–23.

https://doi.org/10.11113/ijic.v12n2.369

Han, J., Tan, Z., Chen, M., Zhao, L., Yang, L., & Chen, S. (2022). Carbon Footprint Research Based on Input–Output Model—A Global Scientometric Visualization Analysis. *International Journal of Environmental Research and Public Health*, *19*(18). https://doi.org/10.3390/ijerph191811343

Hans, M., Hikmawati, E., & Surendro, K. (2023). Predictive Analytics Model for Optimizing Carbon Footprint From Students' Learning Activities in Computer Science-Related Majors. *IEEE Access*, *11*(July), 114976–114991. https://doi.org/10.1109/ACCESS.2023.3324725

Hidayat, A. (2024). Predictions and Policies on Carbon Footprint Release Data at the College of Vocational Studies, IPB University (SV IPB) Based on the Contribution of Campus Operational Activities. *Environment and Ecology Research*, *12*(1), 40–53. https://doi.org/10.13189/eer.2024.120105

Janković, R., Mihajlović, I., Štrbac, N., & Amelio, A. (2021). Machine learning models for ecological footprint prediction based on energy parameters. *Neural Computing and Applications*, *33*(12), 7073–7087. https://doi.org/10.1007/s00521-020-05476-4

Kaur, G. (2024). Integrating Data Envelopment Analysis and Machine Learning Approaches for Energy Optimization, Decreased Carbon Footprints, and Wheat Yield Prediction Across North-Western India. *Journal of Soil Science and Plant Nutrition*, *24*(1), 1424–1447. https://doi.org/10.1007/s42729-024-01647-7

Li, Y., & Sun, Y. (2021). Modeling and predicting city-level CO2 emissions using open access data and machine learning. *Environmental Science and Pollution Research*, *28*(15), 19260–19271. https://doi.org/10.1007/s11356-020-12294-7

Lim, S. J., Cortez, M. M. E., & Esquivel, R. (2023). *Carbon Footprint Prediction in the Philippines Using Time Series in Data Science*. 1296–1303. https://doi.org/10.46254/an13.20230375

Luo, J., Zhuo, W., Liu, S., & Xu, B. (2024). The Optimization of Carbon Emission Prediction in Low Carbon Energy Economy under Big Data. *IEEE Access*, *12*(December 2023), 14690–14702. https://doi.org/10.1109/ACCESS.2024.3351468

Marçal, M. F. M., de Souza, Z. M., Tavares, R. L. M., Farhate, C. V. V., Oliveira, S. R. M., & Galindo, F. S. (2021). Predictive models to estimate carbon stocks in agroforestry systems. *Forests*, *12*(9). https://doi.org/10.3390/f12091240

Meng, Y., & Noman, H. (2022). Predicting CO2 Emission Footprint Using AI through Machine Learning. *Atmosphere*, *13*(11), 1–15. https://doi.org/10.3390/atmos13111871

Mosso, D., Colucci, G., Lerede, D., Nicoli, M., Piscitelli, M. S., & Savoldi, L. (2024). How much do carbon emission reduction strategies comply with sustainable development of the power sector? *Energy Reports*, *11*(March), 3064–3087. https://doi.org/10.1016/j.egyr.2024.02.056

Nguyen, Q., Diaz-Rainey, I., & Kuruppuarachchi, D. (2021). Predicting corporate carbon footprints for climate finance risk analyses: A machine learning approach. *Energy Economics*, *95*, 105129. https://doi.org/10.1016/j.eneco.2021.105129

Ni, K., Hu, Y., Ye, X., AlZubi, H. S., Goddard, P., & Alkahtani, M. (2018). Carbon footprint modeling of a clinical lab. *Energies*, *11*(11). https://doi.org/10.3390/en11113105

Norton, A. J., Anthony Bloom, A., Parazoo, N. C., Levine, P. A., Ma, S., Braghiere, R. K., & Smallman, T. L. (2023). Improved process representation of leaf phenology significantly shifts climate sensitivity of ecosystem carbon balance. *Biogeosciences*, *20*(12), 2455–2484. https://doi.org/10.5194/bg-20-2455-2023

Pirson, T., & Bol, D. (2021). Assessing the embodied carbon footprint of IoT edge devices with a bottom-up life-cycle approach. *Journal of Cleaner Production*, *322*(September), 128966. https://doi.org/10.1016/j.jclepro.2021.128966

Spring, A., Dunkl, I., Li, H., Brovkin, V., & Ilyina, T. (2021). Trivial improvements in predictive skill due to direct reconstruction of the global carbon cycle. *Earth System Dynamics*, *12*(4), 1139–1167. https://doi.org/10.5194/esd-12-1139-2021

Sun, W., & Ren, C. (2021). Short-term prediction of carbon emissions based on the EEMD-PSOBP model. *Environmental Science and Pollution Research*, *28*(40), 56580–56594. https://doi.org/10.1007/s11356-021-14591-1

Thilakarathna, P. S. M., Seo, S., Baduge, K. S. K., Lee, H., Mendis, P., & Foliente, G. (2020). Embodied carbon analysis and benchmarking emissions of high and ultra-high strength concrete using machine learning algorithms. *Journal of Cleaner Production*, *262*(February 2019), 121281. https://doi.org/10.1016/j.jclepro.2020.121281

Tong, M., Duan, H., & He, L. (2021). A novel Grey Verhulst model and its application in forecasting CO2 emissions. *Environmental Science and Pollution Research*, *28*(24), 31370–31379. https://doi.org/10.1007/s11356-020-12137-5

Wang, Y., & Wang, H. (2023). Forecasting CO2 emissions using a novel fractional discrete grey Bernoulli model: A case of Shaanxi in China. *Urban Climate*, *49*. https://doi.org/10.1016/j.uclim.2023.101452

Wen, L., & Yuan, X. (2020). Forecasting CO2 emissions in China's commercial department through BP neural network based on random forest and PSO. *Science of the Total Environment*, *718*, 137194. https://doi.org/10.1016/j.scitotenv.2020.137194

Wilkes, A., Wassie, S., Odhong', C., Fraval, S., & van Dijk, S. (2020). Variation in the carbon footprint of milk production on smallholder dairy farms in central Kenya. *Journal of Cleaner Production*, *265*, 121780. https://doi.org/10.1016/j.jclepro.2020.121780

Yunis, R., Andri, A., & Djoni, D. (2024). Hybridization Model for Air Pollution Prediction Using Time Series Data. *CogITo Smart Journal*, *10*(1), 422–435. https://doi.org/10.31154/cogito.v10i1.619.422-435

Zhang, C. (2023). Carbon Footprint Prediction of Thermal Power Industry under the Dual-Carbon Target: A Case Study of Zhejiang Province, China. *Sustainability (Switzerland)*, *15*(4).

Zhou, W., Zeng, B., Wang, J., Luo, X., & Liu, X. (2021). Forecasting Chinese carbon emissions using a novel grey rolling prediction model. *Chaos, Solitons and Fractals*, *147*, 110968. https://doi.org/10.1016/j.chaos.2021.110968