A Survey of Carbon Performance Assessment and Interpretable Machine Learning for Environmental Impact Analysis

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Abstract

This survey explores the integration of carbon performance assessment, interpretable machine learning, and predictive modeling as essential methodologies for enhancing sustainability and reducing carbon emissions. It highlights the interconnectedness of these approaches in providing comprehensive environmental impact analysis, enabling stakeholders to develop robust strategies for emission reduction. The study emphasizes the need for comprehensive frameworks in evaluating the carbon footprint of large-scale projects and scientific collaborations. In the energy sector, it underscores the dichotomy between technological benefits and manufacturing emissions, advocating for the integration of sustainability in technological advancements. The survey also discusses the influence of corporate sustainability strategies on financial performance and the gap between research and practical application in green technologies. It presents the potential of the DRAA model for large-scale machine learning applications and the environmental benefits of shared micromobility modes. The conclusion stresses the necessity of targeted policy interventions to promote sustainable consumption, particularly among urban middle-class and wealthy households, and calls for the astronomical community to align with sustainability goals. By integrating these methodologies, stakeholders can effectively reduce emissions and advance sustainable practices across various sectors, contributing to ecological responsibility and sustainable development.

1 Introduction

1.1 Interconnected Concepts and Relevance

The intricate relationship between carbon performance, sustainability metrics, and environmental impact analysis is vital for addressing the multifaceted challenges of climate change. Carbon performance, which focuses on measuring and reducing carbon emissions, is essential across diverse sectors, particularly in large-scale computing systems like serverless computing, where the carbon footprint is a significant concern [1]. A comprehensive design strategy that optimizes carbon efficiency, performance, power, and energy is crucial in this context [2].

Sustainability metrics provide critical insights into the environmental impacts of technological advancements, such as the carbon footprint of AI in banking risk management frameworks, aligning with sustainability goals and regulatory requirements [3]. The ability of firms to pass through carbon costs illustrates the integration of carbon performance with sustainability metrics and environmental impact analysis, impacting corporate financial performance [4]. The energy sector's contribution to carbon dioxide emissions, driven by human-induced climate change, necessitates precise measurement of algorithmic carbon footprints [5].

The exponential growth in Deep Learning (DL) model sizes and datasets demands significant computational resources, exacerbating energy consumption and carbon emissions [6]. This rise in DL

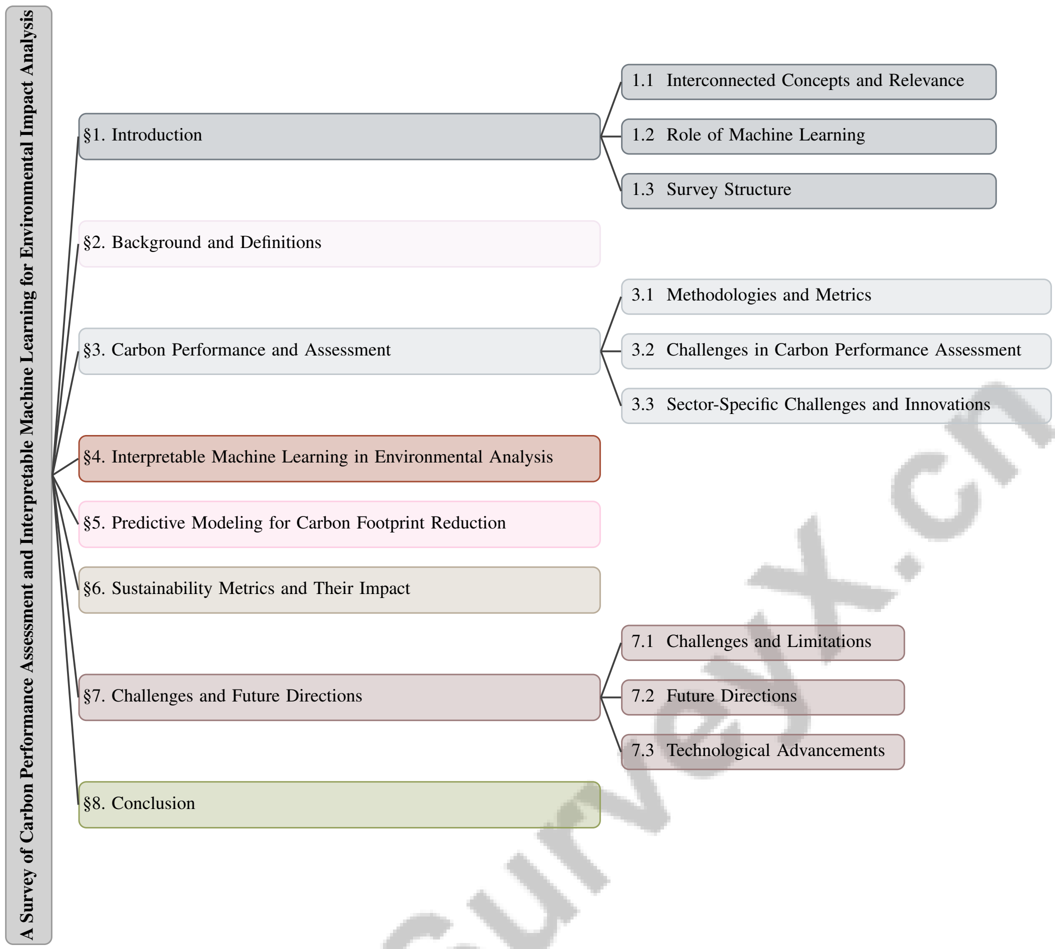

Figure 1: chapter structure

popularity correlates with increased power requirements for model training [7]. The environmental impacts of machine learning on microcontrollers (MCUs) and the potential of TinyML to support sustainable development goals, particularly in carbon reduction, highlight the interconnectedness of these concepts [8].

Assessing the environmental impacts of electronic devices underscores the link between carbon footprint and sustainability metrics [9]. The anthropogenic ecological crisis necessitates comprehensive analyses of various environmental issues, emphasizing the need for benchmarks to facilitate such evaluations [10]. Additionally, the relevance of carbon performance in waste management is demonstrated by using transfer learning models to classify household waste effectively, showcasing the importance of sustainability metrics in waste management [11].

In computing, assessing carbon footprints in heterogeneous integration systems, such as chiplet-based architectures, highlights unique aspects of sustainability metrics [12]. The role of high-performance computing (HPC) systems in reducing carbon emissions further illustrates the interconnectedness of carbon performance and environmental impact [13]. Photonic integrated circuits present sustainable computing solutions by analyzing their carbon footprints to understand broader environmental impacts [14].

The carbon footprint of urban dwellers, influenced by lifestyle choices and travel behaviors, emphasizes the necessity for activity-based carbon assessments in cities [15]. The impact of model architecture and training environments on energy consumption in DL models further highlights the significance of carbon performance in machine learning [16]. Moreover, the carbon footprint of astronomical research infrastructures and predictions of future emissions underscore the interconnectedness of carbon performance and environmental impact analysis [17].

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Integrating carbon performance metrics, sustainability indicators, and comprehensive environmental impact assessments enables stakeholders to devise effective strategies for significantly lowering carbon emissions while fostering sustainable practices across various industries. This approach employs multi-regional input-output analysis to evaluate direct and indirect environmental effects, such as carbon and sulfur oxide emissions, aligning with Industry 4.0 principles that enhance resource efficiency and compliance with sustainable development goals. By addressing supply chain complexities and utilizing eco-innovation platforms, stakeholders can navigate modern production challenges and promote a more sustainable industrial landscape [18, 19]. This integration is crucial for understanding the environmental implications of actions and making informed decisions to enhance ecological responsibility.

1.2 Role of Machine Learning

Machine learning (ML) significantly enhances environmental impact analysis by developing predictive models that optimize energy consumption and carbon emissions across various sectors [20]. Integrating ML techniques into environmental studies facilitates the creation of accurate models essential for understanding and mitigating environmental impacts [21]. However, the rapid increase in ML model sizes has resulted in substantial energy consumption and computational demands, raising sustainability concerns [22].

Recent advancements in ML underscore the importance of transparency and interpretability, crucial for trust and acceptance in applications like HVAC systems [23]. Interpretable ML models address the opacity often associated with advanced techniques, fostering transparency and understanding of predictive models. This transparency is vital for evaluating strategies aimed at achieving carbon neutrality, enabling stakeholders to make informed decisions based on model outputs [24]. Combining unsupervised anomaly detection with interpretable ML models has been proposed to elucidate factors contributing to abnormal fuel consumption, highlighting ML's potential in environmental applications [25].

The Efficiency Analysis Trees (EAT) approach, which merges ML with non-linear programming, exemplifies innovative methodologies enhancing predictive analytics in environmental contexts [26]. Additionally, the development of expert systems like EcoHomeHelper, which organizes and presents advice on reducing greenhouse gas emissions, demonstrates practical ML applications in promoting sustainability [27].

Sustainability concerns associated with deep learning (DL) due to its high carbon footprint are being addressed through green learning initiatives [20]. These initiatives aim to reduce DL's environmental impact by promoting sustainable practices and enhancing model interpretability. Furthermore, benchmarks for evaluating the power consumption of ML models trained using different dataset formats and optimization techniques are essential for improving carbon efficiency in ML applications [28].

Through these advancements, ML remains a critical tool in transforming business practices and addressing complex societal issues, particularly regarding climate change [29]. By enhancing transparency, optimizing energy use, and reducing carbon emissions, ML plays a pivotal role in the pursuit of sustainability and ecological responsibility.

1.3 Survey Structure

This survey provides a comprehensive examination of carbon performance assessment and the role of interpretable machine learning in environmental impact analysis. The survey begins with a detailed exploration of the interconnected concepts of carbon performance, sustainability metrics, and environmental impact analysis, emphasizing the critical role of machine learning in enhancing these areas. It highlights how AI advancements can both contribute to and mitigate environmental challenges by analyzing the carbon footprint of machine learning models, discussing the implications of energy consumption, and presenting strategies for optimizing carbon efficiency. The introduction aims to inform readers about the potential of machine learning to foster sustainable practices and improve environmental governance across various sectors [30, 5, 31, 32, 33]. This sets the stage for understanding the multifaceted challenges and solutions associated with climate change and sustainability.

The second section delves into the background and definitions of core concepts such as carbon performance, carbon footprint, and sustainability metrics, providing foundational understanding necessary for ecological responsibility and decision-making. This is followed by an exploration of methodologies and metrics used to assess carbon performance, addressing challenges and innovations in measuring and improving carbon performance across various sectors.

The fourth section focuses on the role of interpretable machine learning in environmental analysis, highlighting the importance of transparency and interpretability in making predictive models more understandable and effective for decision-making. This section also explores methods to enhance model transparency and interpretability.

The survey examines how predictive modeling techniques are utilized to forecast and mitigate carbon emissions, highlighting case studies where these methodologies have effectively advanced sustainability initiatives. It emphasizes the role of machine learning in optimizing carbon efficiency and reporting practices, as well as the importance of interpretability in predictive analytics to enhance decision-making processes related to environmental governance. Through this exploration, the survey underscores the potential of AI-driven solutions to address the complexities of climate change while promoting transparency and accountability in sustainability efforts [31, 32, 34, 35]. This is followed by an analysis of different sustainability metrics and their effectiveness in measuring environmental impact, discussing how these metrics guide policy and organizational strategies toward sustainability.

The survey concludes by highlighting the current challenges in assessing carbon performance and environmental impacts while proposing future research directions that emphasize innovative advancements in technology and methodology. These advancements aim to enhance the accuracy and effectiveness of carbon footprint evaluations, particularly by addressing issues such as reliance on historical data, complexities of human behavioral responses to AI interventions, and the need for comprehensive measurement strategies. By integrating multilevel perspectives and systems dynamics approaches, the proposed research seeks to foster environmentally responsible practices and governance in AI applications, ultimately contributing to a more sustainable future [31, 36, 33]. This structure ensures a thorough exploration of the topics, providing valuable insights into the integration of carbon performance assessment, interpretable machine learning, and predictive modeling for sustainable environmental outcomes.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Definitions and Concepts

Carbon performance involves strategically managing carbon emissions and energy consumption to optimize resource use and minimize environmental impacts across sectors [13]. It is essential for embedding sustainability into operations and using advanced technologies like AI to enhance environmental governance [17]. The carbon footprint, a critical metric, quantifies total GHG emissions, including direct and indirect sources [37]. Its precise measurement is vital for evaluating the environmental impacts of activities ranging from healthcare services [37] to urban planning [38].

In computing, data centers are projected to significantly contribute to global carbon emissions due to rising energy demands [39]. This highlights the need for sustainable solutions in the manufacturing and operation of computing devices, which are major carbon emission sources [14]. HPC systems also generate substantial carbon emissions, underscoring carbon performance's role in ecological responsibility [13].

Sustainability metrics are crucial for evaluating environmental impacts and informing policy decisions. These metrics, including carbon footprints, serve as indicators of the ecological impacts of activities and infrastructures [17]. The significant inequality in urban residents' activity-based carbon footprints, influenced by factors like income, necessitates targeted interventions to address these disparities [15].

Carbon footprint labels also significantly influence consumer behavior by shaping perceptions and willingness to pay, thereby promoting sustainable consumption patterns [40]. Accurately measuring and managing complex systems' carbon footprints, such as astronomical research infrastructures, remains challenging and requires ongoing research and development [17].

These core definitions and concepts form the basis for understanding carbon performance and environmental impact, emphasizing the need for precise measurement and strategic management to

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achieve sustainability goals. Integrating advanced concepts like AI and Industry 4.0 is crucial for developing strategies that mitigate carbon emissions and foster sustainable practices. By leveraging innovative technologies, organizations can enhance resource and energy efficiency, align operations with sustainable development goals, and address the pressing challenges of climate change [31, 41, 19].

2.2 Sector-Specific Definitions

Carbon performance and footprint evaluation vary significantly across industry sectors, each presenting distinct challenges and methodologies. In tourism, emissions primarily arise from transport, shopping, and food, excluding non-tourism-related activities [42]. This necessitates tailored strategies for effective emission management and reduction.

In software and computing, carbon footprint measurement involves four categories: software energy consumption, server overhead energy consumption, energy mix, and emissions from embodied carbon [43]. Understanding these categories is crucial for assessing digital infrastructures' environmental impacts and devising strategies to enhance energy efficiency and reduce emissions in the software industry.

The manufacturing sector faces challenges in carbon footprint accounting, particularly with traditional life cycle assessment (LCA) methods that rely heavily on human expertise, complicating real-time updates [44]. This limitation calls for dynamic and automated LCA approaches to accurately capture manufacturing processes and products' environmental impacts.

The diverse sector-specific definitions of carbon performance assessment highlight the varying methodologies and metrics across industries, emphasizing the need for context-specific approaches to effectively measure and enhance sustainability outcomes. This is particularly evident in supply chains, where direct and indirect emissions, resource consumption, and compliance with evolving sustainability regulations require tailored assessment frameworks. Multi-regional input-output analysis reveals significant discrepancies in carbon emissions across sectors, while standardized sustainability metrics, such as those mandated by the EU taxonomy regulation, aim to streamline reporting and improve investment decisions. Additionally, Industry 4.0 advancements present opportunities and challenges for sustainability, necessitating innovative, real-time solutions for carbon footprint accounting that can adapt to the intricate and evolving landscape of environmental performance [19, 45, 44, 18, 26]. Recognizing each sector's unique characteristics and challenges enables stakeholders to formulate more effective strategies to reduce carbon emissions and promote sustainable practices tailored to their specific contexts.

In recent years, the assessment of carbon performance has gained significant attention due to its implications for sustainability and environmental policy. A comprehensive understanding of this topic necessitates an exploration of various methodologies and metrics employed in the field. As illustrated in Figure 2, the hierarchical structure of carbon performance assessment is delineated, categorizing methodologies and metrics while also addressing the challenges faced and the innovations specific to different sectors. This figure highlights essential tools, such as DeltaLCA and IRMS, which are pivotal in evaluating carbon performance. Additionally, it underscores challenges like real-time adaptation, alongside sector-specific solutions in information and communication technology (ICT) and manufacturing. By integrating these elements, we can better appreciate the complexities and advancements in carbon performance assessment that are critical for effective environmental management.

3 Carbon Performance and Assessment

3.1 Methodologies and Metrics

The assessment of carbon performance involves diverse methodologies and metrics that address specific environmental challenges and operational contexts, essential for formulating strategies to reduce emissions and enhance sustainability. DeltaLCA exemplifies a user-in-the-loop design tool that automates life cycle inventory generation, facilitating comparative analyses and streamlining carbon footprint assessments [9]. In autonomous transportation, simplified life cycle assessments evaluate bicycle-sharing systems' environmental performance, highlighting the need for sector-specific approaches [48]. Data centers benefit from Integrated Resource Management Systems

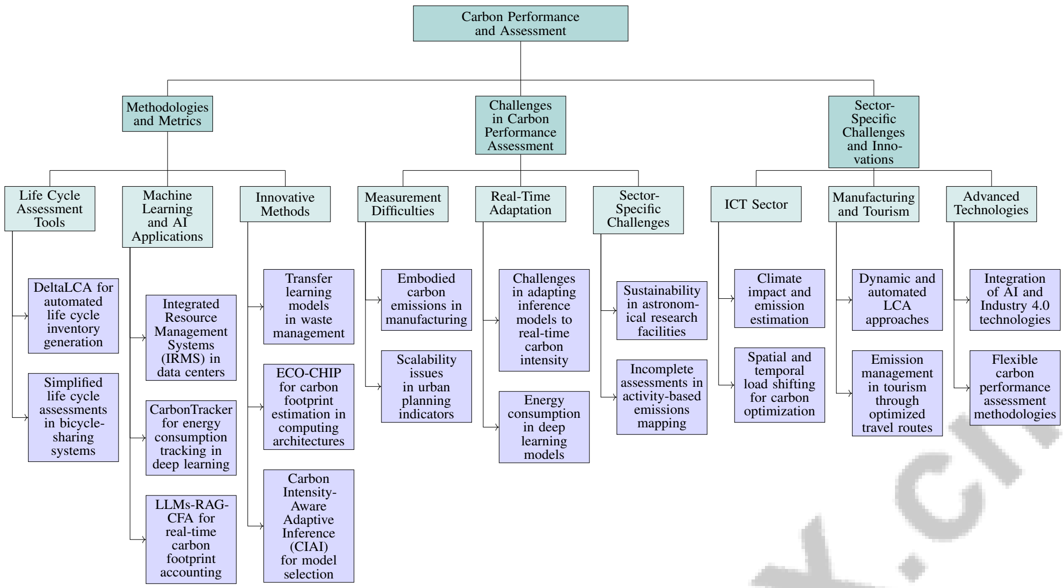

Figure 2: This figure illustrates the hierarchical structure of carbon performance assessment, categorizing methodologies and metrics, challenges, and sector-specific innovations. It highlights tools like DeltaLCA and IRMS, challenges such as real-time adaptation, and sector-specific solutions in ICT and manufacturing.

Method Name	Methodological Diversity	Technology Integration	Sector-Specific Applications
DLC[9]	Comparative Analyses Designs	Automates Life Cycle	Electronics Designs Evaluation
IRMS[46]	Varied Approaches	Machine Learning Techniques	Data Centre Resources
CFA[44]	Varied Approaches	Large Language Models	Five Industries
ECO-CHIP[12]	Varied Approaches	Advanced Modeling Techniques	Mobile Processors, Gpus
CIAI[47]	Heuristic Algorithm	Reinforcement Learning	Various Domains

Table 1: Overview of methodologies employed in carbon performance assessment, highlighting their methodological diversity, technology integration, and sector-specific applications. The table categorizes five distinct methods, illustrating their unique contributions to sustainability and emission reduction across various domains.

(IRMS) using machine learning and reinforcement learning to dynamically manage resources, thereby enhancing energy efficiency [46].

In deep learning, the CarbonTracker benchmark tracks and predicts energy consumption and emissions during model training, promoting responsible computing [7]. The LLMs-RAG-CFA method integrates large language models with retrieval-augmented generation technology for real-time carbon footprint accounting, demonstrating AI's potential in improving environmental assessment accuracy [44]. Waste management employs transfer learning models for garbage classification, balancing accuracy and computational carbon emissions [11]. The ECO-CHIP tool estimates carbon footprints for heterogeneous computing architectures, considering design and manufacturing efficiencies [12]. Additionally, the Carbon Intensity-Aware Adaptive Inference (CIAI) method selects deep neural network models based on real-time carbon intensity, optimizing accuracy and emissions [47].

These methodologies provide a comprehensive framework for assessing carbon performance, allowing stakeholders to devise effective emission reduction strategies. Advanced modeling techniques and environmental considerations enhance the accuracy and reliability of assessments, facilitating real-time updates and improved information retrieval. Machine learning studies underscore the importance of transparent carbon emissions reporting and optimized carbon efficiency, fostering sustainable practices [44, 32].

As illustrated in Figure 3, which categorizes methodologies and metrics in carbon performance assessment, the focus is on life cycle assessment, energy management, and AI/machine learning applications. The hierarchical structure emphasizes the specific tools and methods within each category, highlighting their roles in enhancing sustainability and reducing emissions. The first image in the figure depicts a product's lifecycle, emphasizing the need to consider each phase, from raw material extraction to disposal, for accurate carbon footprint assessment. The second image offers a comparative view of CO2 emissions across countries, contrasting data from the United States, Europe, and a global average, exemplifying diverse evaluation methodologies [49, 5]. Table 1 provides a comprehensive overview of various methodologies employed in carbon performance assessment, demonstrating their integration of diverse approaches, technological innovations, and specific applications across different sectors.

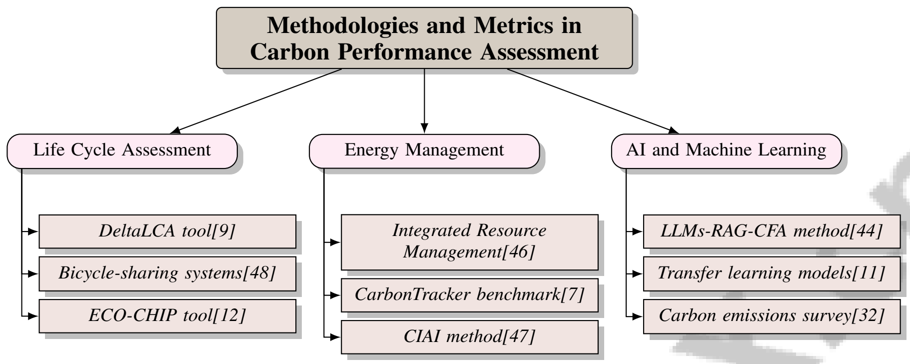

Figure 3: This figure illustrates the hierarchical categorization of methodologies and metrics in carbon performance assessment, focusing on life cycle assessment, energy management, and AI/machine learning applications. Each category includes specific tools and methods, highlighting their roles in enhancing sustainability and reducing emissions.

3.2 Challenges in Carbon Performance Assessment

Carbon performance assessment faces significant challenges, primarily in accurately measuring carbon footprints across diverse contexts. In high-performance computing (HPC), integrating carbon efficiency into design and operations is critical for emissions reduction [13]. Current methods often inadequately address embodied carbon emissions from manufacturing, which can surpass operational emissions, particularly in photonic integrated circuits [14]. In urban planning, the lack of replicability and reliability in scaling indicators, such as the box-counting method, impedes effective adoption [38]. Traditional survey data for mapping activity-based emissions often miss complexities of individual travel behaviors, leading to incomplete assessments [15].

The dynamic nature of real-time carbon intensity presents another challenge, as existing methods struggle to adapt inference models based on fluctuations, limiting their potential for optimizing carbon efficiency in real-time applications [47]. Deep learning models face substantial challenges due to their high energy consumption and resultant carbon footprints, necessitating energy-efficient training environments [16]. The expansion of astronomical research facilities further complicates sustainability efforts, as their growth may increase emissions [17]. Addressing these challenges requires innovative benchmarks and methodologies incorporating comprehensive data on energy consumption and emissions. Solutions may include enhancing data collection techniques, adopting advanced technologies for real-time monitoring, and integrating carbon efficiency considerations into design and operational stages, enabling effective emission mitigation strategies.

3.3 Sector-Specific Challenges and Innovations

Carbon performance assessment and optimization present unique challenges across sectors, necessitating innovative solutions. In the information and communication technology (ICT) sector, climate impact is significant, requiring nuanced methodologies for emission estimation and assumptions underlying future projections [50]. Rapid technological advancements necessitate continuous updates to emission estimation methodologies to accurately reflect the evolving landscape. Innovations include spatial load shifting, temporal load shifting, and resource autoscaling as carbon optimization techniques, evaluated under attribution methods for enhancing energy efficiency [51]. Spatial load shifting relocates computational tasks to regions with lower carbon intensity, temporal load shifting schedules tasks during lower carbon intensity periods, and resource autoscaling dynamically adjusts resources to match demand, optimizing energy use.

In manufacturing, traditional life cycle assessment (LCA) methods face challenges in real-time updates due to reliance on human expertise. This limitation has led to dynamic and automated LCA approaches that accurately capture environmental impacts [44]. These methods leverage AI and machine learning for enhanced accuracy and efficiency in carbon footprint assessments. The tourism sector faces specific challenges, with emissions primarily from transport, shopping, and food. Tailored strategies are essential for managing emissions, emphasizing sector-specific methodologies [42]. Innovations focus on optimizing travel routes, promoting sustainable tourism practices, and integrating carbon offset programs.

Addressing sector-specific challenges requires innovative methodologies and tailored strategies considering each sector's unique characteristics. By integrating advanced technologies such as large language models and retrieval-augmented generation with flexible carbon performance assessment methodologies, stakeholders can create precise and adaptive emissions reduction strategies. This approach enhances the accuracy and real-time responsiveness of carbon footprint accounting across industries—including aluminum, lithium batteries, and renewable energy—and fosters sustainable practices aligned with evolving environmental governance frameworks. Leveraging AI and Industry 4.0 technologies facilitates innovative solutions to complex sustainability challenges, promoting efficient resource use and enhancing environmental performance [19, 31, 50, 33, 44].

4 Interpretable Machine Learning in Environmental Analysis

4.1 Importance of Transparency and Interpretability

In environmental analysis, the transparency and interpretability of machine learning models are pivotal for fostering trust and enabling informed decision-making among stakeholders, which is crucial for ecological responsibility. The complexity inherent in these models often obscures their decision-making processes, potentially undermining user confidence and hindering model refinement [52]. Understanding model predictions is as crucial as the predictions themselves, especially in contexts prioritizing sustainability and carbon reduction [5].

Tools such as ECO-CHIP enhance transparency by offering detailed evaluations of both embodied and operational carbon emissions, thereby increasing the reliability of carbon footprint estimates [12]. The integration of digital twins and AI in energy efficiency and carbon emissions management exemplifies the transformative potential of transparent systems in achieving carbon neutrality [39].

Incorporating carbon considerations into the design and operation of high-performance computing (HPC) systems aligns with the need for transparency in machine learning to secure sustainable outcomes [13]. Photonics-based accelerators, such as ADEPT, showcase lower carbon footprints compared to traditional CMOS accelerators, underscoring the necessity of transparent evaluations of their environmental benefits [14].

The heuristic model selection based on carbon intensity, as proposed by [47], highlights how transparency in model selection can enhance carbon emission efficiency without compromising accuracy, particularly relevant for vision recognition services. In urban planning, replicability and accuracy in scaling indicators are essential for effective policymaking, emphasizing the broader importance of transparent methodologies in environmental impact assessments [38]. Moreover, transparency in evaluating deep learning architectures aids in understanding energy efficiency and model correctness, which are crucial for environmental impact analysis [16].

The carbon emissions associated with astronomical infrastructures underscore the need for transparent assessments to fully comprehend their environmental impacts [17].

Figure 4 illustrates the key areas of transparency and interpretability in environmental analysis, highlighting the role of model transparency, carbon reduction strategies, and urban planning methodologies in fostering ecological responsibility and sustainability. By enhancing transparency and interpretability, machine learning models can better support environmental analysis, enabling stakeholders to devise robust strategies for emission reduction and sustainability.

4.2 Enhancing Model Transparency and Interpretability

Enhancing transparency and interpretability in machine learning models is crucial for their effective application in environmental analysis, where understanding predictions is key to informed

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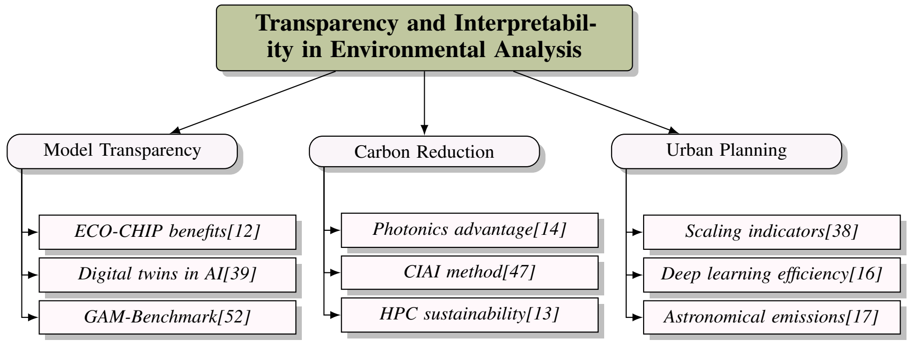


Figure 4: This figure illustrates the key areas of transparency and interpretability in environmental analysis, highlighting the role of model transparency, carbon reduction strategies, and urban planning methodologies in fostering ecological responsibility and sustainability.

decision-making. Techniques such as Local Interpretable Model-Agnostic Explanations (LIME) and permutation feature importance illuminate model predictions, allowing stakeholders to understand influencing factors [34]. These methodologies demystify complex models, ensuring users can trust and leverage predictive outputs effectively.

Integrating domain knowledge with machine learning explanations further strengthens the interpretability of black-box models. Explainable AI-enabled inspection methods combine domain expertise with model outputs to elucidate predictions, offering a deeper understanding of underlying mechanisms [53]. This is particularly beneficial in sectors like energy management, where understanding causal relationships is vital for optimizing resource utilization and minimizing emissions.

Hybrid Predictive Models (HPM) provide a dynamic approach to model interpretability, enabling systems to switch between interpretable and black-box models based on data characteristics, thus balancing transparency with predictive performance [35]. This flexibility is crucial in environmental contexts, where model interpretability can directly affect policy and operational decisions.

Innovative methods such as the DRAA, involving real-time analysis and adaptive resource management, significantly enhance transparency and interpretability in machine learning applications [54]. The CFO method improves transparency by employing a dual-subgradient algorithm on a stage-expanded graph that incorporates charging options [55].

In serverless computing, ECOLIFE's extensions to Particle Swarm Optimization (PSO) are designed for serverless environments, dynamically enhancing model transparency and interpretability based on varying function invocation patterns and carbon intensity [1]. This adaptability is crucial for optimizing carbon efficiency in real-time applications.

The method proposed by [26] combines high classification accuracy with explainability, thereby enhancing user trust in automated carbon footprint estimations. Additionally, the benchmark introduced by [52] provides a systematic evaluation framework that encompasses a diverse set of datasets and a thorough comparison of multiple Generalized Additive Models (GAMs) against traditional models, contributing to the understanding of performance and interpretability trade-offs.

Recent advancements in enhancing model transparency and interpretability are vital for effective environmental analysis, empowering stakeholders—from policymakers to industry leaders—to critically assess automated systems. This capability enables the derivation of actionable insights for developing comprehensive strategies aimed at emission reduction and sustainability. By facilitating a deeper understanding of machine learning models, these enhancements address the complexities of environmental governance and support the creation of culturally appropriate practices that minimize resource and energy consumption [56, 31, 57, 32]. Future research should focus on these areas to develop more transparent and interpretable models, ultimately fostering more effective and sustainable decision-making across various sectors.

5 Predictive Modeling for Carbon Footprint Reduction

5.1 Predictive Modeling for Sustainability

Predictive modeling is pivotal in advancing sustainability by providing frameworks for precise forecasting and strategic interventions aimed at reducing carbon emissions across sectors. These models enable organizations to develop comprehensive sustainability strategies, identify carbon footprints, and implement targeted interventions. For instance, Ichnos offers task-level insights into significant carbon emission contributors, facilitating precise interventions [58]. In waste management, predictive models enhance sustainability by optimizing the balance between operational carbon emissions and classification performance [11].

In healthcare, predictive modeling aids in formulating strategies to reduce high-emission service demands and foster sustainable supply chain practices, aligning with ecological goals [37]. Transportation sectors benefit from these models by evaluating shared micromobility solutions, such as autonomous bicycle-sharing systems, which demonstrate considerable emission reductions [48].

Predictive models also optimize electronic waste management and carbon emissions in mini data centers, as seen in projects like Genesis, which promote the reuse of older servers with renewable energy [59]. In serverless computing, frameworks like ECOLIFE utilize predictive modeling to optimize scheduling, minimizing carbon emissions [1]. Additionally, integrating spatial and temporal carbon intensity information in edge computing networks significantly reduces carbon footprints [60]. Platforms like CarbonKit exemplify the versatility of predictive modeling in reducing personal carbon emissions [61].

To illustrate the comprehensive nature of predictive modeling in sustainability, Figure 5 presents a hierarchical structure categorizing key areas of focus such as carbon emission reduction, sectoral applications, and methodological innovations, each supported by specific studies and tools. These techniques are indispensable for sustainability, enabling stakeholders to forecast, manage, and effectively reduce carbon emissions. By employing advanced methodologies such as interpretable machine learning and hybrid predictive models, predictive modeling enhances ecological responsibility and sustainable development. These methods improve prediction accuracy and ensure transparency, allowing stakeholders to comprehend decision-making factors, crucial for addressing ecological challenges and fostering responsible practices [34, 35].

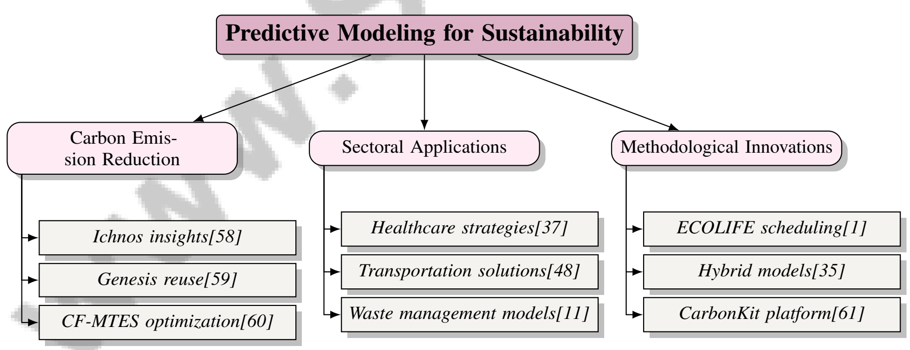
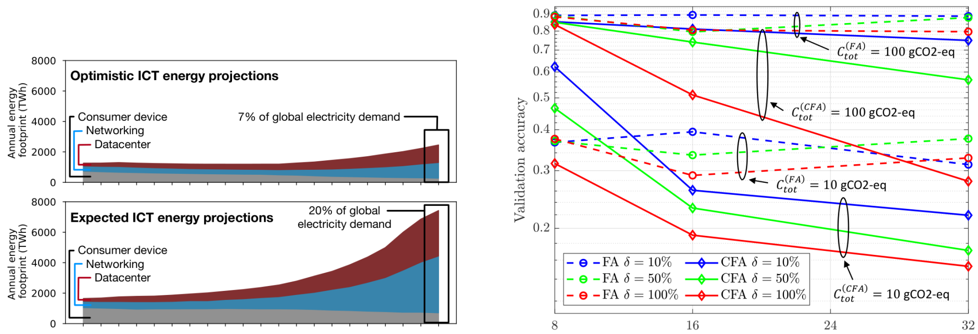


Figure 5: This figure illustrates the hierarchical structure of predictive modeling for sustainability, categorizing key areas of focus such as carbon emission reduction, sectoral applications, and methodological innovations, each supported by specific studies and tools.

5.2 Applications in Carbon Emission Estimation

Predictive modeling is essential for estimating carbon emissions, providing frameworks to identify sources and develop reduction strategies. In distributed cloud storage, the Cubbit model achieves a 77

Predictive models also enhance shared micromobility solutions by analyzing usage patterns and vehicle design, promoting sustainable urban mobility [48]. In healthcare, these models guide sustainability initiatives by forecasting environmental impacts [37]. Furthermore, in electronic waste management, predictive models optimize emissions in mini data centers, as demonstrated by Genesis, which facilitates the reuse of older servers powered by renewable energy [59].



(a) ICT energy projections: Optimistic and Expected[36]

(b) Validation accuracy of different methods for different values of CFA and FA[62]

Figure 6: Examples of Applications in Carbon Emission Estimation

As illustrated in Figure 6, predictive modeling significantly aids in carbon footprint reduction through accurate emissions estimation. The first image compares ICT energy projections under optimistic and expected scenarios, highlighting potential savings. The second image evaluates various predictive methods' accuracy in carbon footprint analysis, showcasing their effectiveness in emissions prediction. These examples underline predictive modeling's role in developing emission reduction strategies, emphasizing the need for reliable estimation tools in sustainability [36, 62].

5.3 Case Studies and Results

Case studies offer insights into predictive modeling's successful applications for carbon footprint reduction. IoTCO2 exemplifies this by accurately estimating carbon footprints across contexts, demonstrating its practical utility [63]. Another case study, the CFO method, achieves up to 28

These studies highlight predictive modeling's transformative impact on sustainability, emphasizing the integration of advanced analytical techniques into environmental strategies. By showcasing practical applications, these case studies enhance understanding of predictive models' strategic use in driving sustainability improvements across sectors. They underscore advanced technologies like Industry 4.0, machine learning, and AI in addressing environmental challenges, analyzing models' carbon footprints, promoting carbon-efficient practices, and aligning technological advancements with sustainable goals. These insights are crucial for stakeholders aiming to implement solutions balancing technological progress with environmental stewardship [31, 33, 32, 19].

6 Sustainability Metrics and Their Impact

6.1 Overview of Sustainability Metrics

Sustainability metrics are pivotal in quantifying the ecological impact of various activities and technologies, forming the backbone of carbon reduction strategies across sectors. These metrics encompass both operational and embodied carbon footprints, as seen in the evaluation of photonic technologies, which stresses the need for a comprehensive assessment of computing systems' total carbon emissions [14]. In the semiconductor sector, tools like ECO-CHIP offer architectural-level analyses to estimate total carbon footprints, highlighting areas for improvement in manufacturing and operational sustainability [12].

In healthcare, sustainability metrics are crucial, as evidenced by the 15

Consumer behavior is also influenced by sustainability metrics, as shown by the willingness to pay for carbon footprint-labeled foods across countries, indicating the potential of these metrics to drive market trends toward sustainable products [40]. Urban planning benefits from metrics like the scaling indicator, which informs resilience and sustainability attributes [38]. These metrics guide policy decisions and urban development strategies, fostering sustainable cities.

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By quantifying the ecological footprints of diverse activities and technologies, sustainability metrics enhance the effectiveness of sustainability initiatives, enabling stakeholders to develop robust emission reduction strategies. They support informed decision-making for investors, as seen in the EU's taxonomy regulation, which mandates the disclosure of green revenues, promoting investment in sustainable practices. Multi-regional input-output analysis allows for detailed environmental impact assessments across global supply chains, highlighting emissions in critical sectors and aligning sustainability efforts with broader ecological and societal goals [18, 45, 64].

6.2 Effectiveness of Sustainability Metrics

Benchmark	Size	Domain	Task Format	Metric
MIA-CF[65]	484	Medical Image Analysis	Image Segmentation	Carbon Emissions, Energy Consumption
BLOOM[66]	1,600,000	Natural Language Processing	Language Modeling	CO2eq emissions
GHG-PLAST[67]	1,000	Environmental Science	Life Cycle Assessment	GHG Emissions, Carbon Footprint
FL-CO2e[68]	671,000	Image Classification	Image Classification	CO2e emissions, Energy consumption
ML-CF[28]	89,885	Image Classification	Classification	Power Consumption, Carbon Footprint
DP-CE[69]	15,000	Natural Language Processing	Topic Classification	Carbon Emissions, Accuracy
LPM[70]	120	Medical Imaging	Image Synthesis	CO2 emissions, Power Consumption
CryptoBench[71]	1,000,000	Electricity Market Analysis	Carbon Footprint Analysis	Carbon Footprint, Reliability Index

Table 2: This table presents a comprehensive overview of various benchmarks utilized across different domains to assess sustainability metrics. It details the benchmark names, sizes, domains, task formats, and the specific metrics employed to measure carbon emissions and energy consumption. These benchmarks illustrate the diverse applications and methodologies in evaluating ecological impacts, highlighting the importance of standardized practices in sustainability assessments.

The effectiveness of sustainability metrics in achieving environmental objectives depends on their ability to provide accurate assessments of ecological impacts across domains. However, the lack of standardized accounting practices for carbon emissions poses significant challenges, as highlighted by current studies [36]. This inconsistency can undermine coherent strategies for emission reduction and ecological responsibility.

Despite these challenges, sustainability metrics remain critical for guiding policy and organizational strategies toward sustainability. Metrics such as carbon footprint, energy usage, and carbon intensity offer insights into the environmental implications of activities, enabling stakeholders to identify improvement areas. In the semiconductor industry, tools like ECO-CHIP facilitate architectural-level analyses for informed decision-making [12]. In healthcare, integrating sustainability metrics into planning is essential for addressing emissions linked to medical services and pharmaceuticals [37], empowering organizations to implement targeted interventions.

Sustainability metrics also influence consumer behavior, as seen in the interest in carbon footprint-labeled foods across countries [40]. This illustrates their potential to drive market trends toward sustainable products, contributing to broader environmental goals. While the lack of standardized practices challenges their effectiveness, sustainability metrics remain indispensable for achieving environmental objectives. They establish a framework for evaluating ecological impacts, empowering stakeholders to formulate strategies aligned with sustainability goals. This alignment facilitates informed investment decisions, as seen in the EU Taxonomy Regulation, and enhances the ability to measure and manage environmental performance across global supply chains. Table 2 provides a detailed overview of representative benchmarks used to evaluate sustainability metrics across multiple domains. These metrics support the decoupling of economic growth from resource consumption, fostering ecological responsibility and sustainable development [72, 19, 45, 44, 18].

6.3 Guiding Policy and Organizational Strategies

Sustainability metrics are essential for informing policy-making and organizational strategies, aligning environmental goals with actionable plans. They provide quantitative assessments of ecological impacts, enabling the development of strategies to mitigate emissions from various sources, including digital activities, and promote sustainable practices through informed decision-making and standardized reporting [73, 45, 64, 74, 44]. Integrating these metrics into policy frameworks guides legislative efforts to reduce carbon footprints and achieve broader environmental objectives.

A significant application of sustainability metrics is in carbon labeling policies, influencing consumer behavior and driving market trends toward sustainable products [40]. These labels provide transparent information on carbon footprints, empowering consumers to make informed choices and encouraging producers to adopt sustainable practices. This shift can lead to substantial emission reductions, aligning market dynamics with environmental goals.

In healthcare, sustainability metrics inform policy decisions related to the environmental impacts of services and pharmaceuticals. By quantifying carbon footprints, these metrics enable policymakers to identify intervention areas and implement strategies to mitigate emissions [37]. This enhances healthcare systems' sustainability and aligns with public health objectives by reducing the ecological burden of medical services.

Urban planning also benefits from sustainability metrics, informing the development of resilient and sustainable cities. Metrics like the scaling indicator provide insights into urban resilience, influencing policy decisions related to infrastructure and resource management [38]. Incorporating these metrics into planning promotes sustainable urban growth and enhances residents' quality of life.

Organizations benefit from integrating sustainability metrics, providing a framework for assessing and improving environmental performance. In the semiconductor industry, tools like ECO-CHIP estimate total carbon footprints, enabling organizations to identify emission reduction opportunities and enhance sustainability [12]. Leveraging these insights allows organizations to develop strategic plans aligning operations with sustainability goals.

Sustainability metrics are essential for shaping policy and organizational strategies, offering data-driven insights for effective environmental management. The EU's taxonomy regulation mandates the disclosure of standardized sustainability metrics, aiding investors in making informed decisions and steering investments toward sustainable activities. Advanced methodologies like multi-regional input-output analysis assess environmental performance across global supply chains, quantifying impacts like carbon emissions and resource consumption. These metrics help organizations understand their environmental footprint and improve sustainability practices, contributing to a more effective transition to a green economy [18, 45]. By aligning policies and strategies with these metrics, stakeholders can drive progress toward sustainability objectives and foster a sustainable future.

7 Challenges and Future Directions

7.1 Challenges and Limitations

Assessing carbon performance and environmental impacts faces significant challenges due to the complexities of accurately capturing emissions across diverse sectors. A major issue is the lack of standardized reporting practices, leading to inconsistencies and incomplete data in carbon emissions reporting, complicating comprehensive model development for emissions reduction. Studies often rely on aggregated national inventories rather than sector-specific data, limiting precision, especially in agriculture where site-specific factors significantly affect carbon estimates [8]. In the energy sector, models typically assume constant carbon intensity, failing to reflect emissions' dynamic nature, resulting in inaccuracies [22].

Integrating new technologies with sustainable practices presents further challenges. The high carbon footprint from IoT device production and increased energy consumption from IoT integration are significant limitations [8]. In computing, enhancing carbon efficiency is hindered by constraints on achieving further efficiency gains and lacking financial incentives [2]. Data centers struggle with optimizing carbon performance due to neglecting power imbalance costs [7]. Reliance on external APIs for accurate carbon intensity data complicates emissions tracking and prediction due to potential unavailability or unreliability [5].

The complexity of deriving insights from heterogeneous datasets and real-time data integration challenges limits current research effectiveness [9]. The lack of real-time visibility into power purchase agreements and residual energy mixes leads to inaccuracies in carbon intensity estimates, potentially overestimating emission reductions. Existing research practices and facility growth contribute to unsustainable emissions, posing significant challenges [17].

Machine learning research faces limitations such as small sample sizes, lack of generalizability, and insufficient attention to ethical implications. The complexity of factors influencing greenhouse gas emissions, like economic growth and energy consumption, poses challenges for effective policy formulation. Estimates may not capture all emissions sources, particularly during manufacturing [8]. Key challenges include persistent emissions inequality and structural forces reinforcing carbon footprint disparities. The method's reliance on user engagement and comparison accuracy further highlights current challenges [9].

User survey data dependence introduces biases and uncertainties in estimating modal shifts and emissions, indicating difficulties in accurately capturing transportation-related emissions [48]. Platforms like CarbonKit face privacy and data security barriers, underscoring challenges in engaging individuals in sustainable practices. In computational fluid dynamics, the lack of comprehensive energy consumption and emissions data across applications complicates accurate carbon emissions estimation from high-performance computing [6]. Assuming uniform energy consumption for tasks may not hold true in all scenarios, affecting optimization accuracy in edge computing [22]. Methods may be constrained by the availability and quality of fine-grained carbon intensity data, which may not always be accessible. Finally, analysis limitations arise from using a single GPU configuration, which may not represent broader scenarios in machine learning training environments.

7.2 Future Directions

Future research in carbon performance assessment and environmental impact analysis should focus on developing holistic frameworks that integrate technological advancements with policy initiatives. This includes exploring innovative carbon capture approaches and enhancing AI's role in optimizing energy management [39]. In high-performance computing, there is a pressing need for reliable carbon measurement tools and innovative hardware designs to improve carbon performance assessment [13].

Photonic computing offers unique sustainability opportunities, and future research should aim to develop more accurate carbon footprint models for photonic chips, exploring design strategies that integrate photonics with electronic components to optimize environmental benefits [14]. In urban planning, refining the scaling indicator and exploring its applications in diverse contexts are essential steps. Integrating this indicator into broader sustainability frameworks will provide valuable insights into urban resilience and sustainability [38].

Examining activity-based carbon footprints across urban areas will illuminate urban design implications on sustainability and equity, crucial for developing planning strategies promoting environmental sustainability and social equity [15]. In adaptive inference, future work will explore its application across domains, utilizing non-linear optimization techniques like reinforcement learning to maximize carbon emission efficiency [47].

In deep learning, exploring additional architectures and diverse training environments will be critical for enhancing energy efficiency and addressing current limitations [16]. Aligning research efforts with global climate targets will involve developing sustainable practices and enhancing decarbonization efforts, proposing future directions that align with these objectives [17].

By pursuing these research directions, the field can significantly enhance the effectiveness and sustainability of environmental management practices. This progress will facilitate integrating innovative technologies, such as AI, into organizational processes and promote a culture of ecological governance. Ultimately, these advancements will align with global efforts toward ecological responsibility and sustainable development, addressing urgent challenges like climate change and resource depletion while fostering economic opportunities and stakeholder engagement within large organizations [31, 41, 33].

7.3 Technological Advancements

Integrating emerging technologies into environmental impact analysis holds significant promise for enhancing sustainability efforts' precision and effectiveness. One notable advancement is digital twins, virtual representations of physical systems capable of simulating and predicting environmental impacts in real-time. Leveraging digital twins allows organizations to optimize energy consumption and reduce carbon emissions, aligning with broader sustainability goals [39].

In computing, photonic technologies are emerging as sustainable alternatives to traditional electronic components. Photonic integrated circuits offer a lower carbon footprint and improved energy efficiency, presenting a promising solution for mitigating data centers' and high-performance computing systems' environmental impact [14]. Adopting photonics in computing architectures is expected to revolutionize the industry by providing more sustainable computing solutions.

Machine learning and artificial intelligence (AI) continue to play pivotal roles in environmental impact analysis. Developing interpretable machine learning models, such as those employing Local Interpretable Model-Agnostic Explanations (LIME), enhances transparency and trust in predictive analytics. These models facilitate better decision-making by providing insights into the factors driving environmental outcomes [34]. Additionally, integrating AI with causality learning offers a new perspective on optimizing resource utilization and minimizing emissions, further advancing the field of environmental analysis [75].

Using Internet of Things (IoT) devices in environmental monitoring is another technological advancement with substantial potential. IoT devices provide real-time data on energy consumption and emissions, enabling more accurate assessments of environmental impacts [8]. Despite challenges associated with the carbon footprint of IoT production, the benefits of real-time monitoring and data-driven decision-making are significant.

Moreover, applying edge computing in environmental analysis offers opportunities for reducing latency and improving data processing efficiency. By processing data closer to the source, edge computing can lower the energy consumption associated with data transmission and enhance digital infrastructures' sustainability [60].

These technological advancements underscore innovation's transformative potential in enhancing environmental impact analysis, particularly through AI application. AI can significantly improve the accuracy and efficiency of environmental assessments by integrating data-driven insights, optimizing resource use, and fostering sustainable practices across various industries. By addressing environmental challenges' complexities and leveraging AI's capabilities, more effective strategies for reducing carbon footprints and promoting environmental governance can be developed [31, 33]. By embracing new technologies and integrating them with existing methodologies, stakeholders can devise more effective strategies for reducing carbon emissions and promoting sustainable practices across various sectors.

8 Conclusion

The survey highlights the essential integration of carbon performance assessment, interpretable machine learning, and predictive modeling as crucial strategies for achieving sustainable environmental outcomes. This interconnected approach facilitates comprehensive environmental impact analysis, enabling stakeholders to formulate robust emission reduction strategies. The examination of the carbon footprint associated with large-scale physics projects underscores the necessity for comprehensive frameworks in environmental impact analysis, emphasizing potential reduction strategies [76]. The significant carbon impact identified in scientific conferences further illustrates the urgent need for actionable strategies that preserve the benefits of scientific collaboration while minimizing emissions [77].

In the energy sector, the contrast between the advantages of silicon photovoltaic technology and the emissions produced during manufacturing processes highlights the importance of embedding sustainability into technological advancements [78]. This aligns with the broader objective of ensuring that innovations contribute positively to climate goals [79]. Moreover, cultivating a sustainability mindset within the AI community is vital to prevent technological progress from exacerbating climate change [80].

Corporate strategies that incorporate sustainability not only enhance social and environmental outcomes but also positively influence financial performance, as indicated by the relationship between carbon emission performance and financial metrics [4]. However, the disconnect between theoretical research and practical application in green technologies necessitates efforts to bridge this gap to fully realize the potential of sustainable innovations [81].

AI-generated, for reference only.

Experiments with the DRAA model demonstrate its viability for large-scale machine learning applications, showcasing notable improvements in efficiency and scalability [54]. Additionally, shared micromobility modes present environmental advantages over private vehicles, contingent upon vehicle design and usage patterns, highlighting the role of predictive modeling in optimizing sustainable transportation solutions [82].

The survey concludes that targeted policy interventions are necessary to promote sustainable consumption practices, particularly among urban middle-class and affluent households, who account for the majority of carbon emissions [83]. Insights into the significant carbon footprint gap influenced by urban design and income disparities further underscore the need for targeted urban planning strategies [15]. Furthermore, the astronomical community is urged to reflect on its practices to align with sustainability goals and mitigate its environmental impact [17]. By integrating carbon performance assessment, interpretable machine learning, and predictive modeling, stakeholders can develop effective strategies to reduce emissions and foster sustainable practices across various sectors, ultimately contributing to ecological responsibility and sustainable development.

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