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Artificial Intelligence in Carbon Emissions Monitoring and Reduction: A Systematic Review

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ABSTRACT

Artificial intelligence (AI) is increasingly recognized as a transformative technology for monitoring carbon emissions, improving emissions accounting, and supporting strategies for climate change mitigation. This systematic review examines the applications of AI in carbon emissions monitoring and reduction, focusing on its principal technologies, implementation approaches, potential benefits, and associated challenges. The review synthesizes existing literature on machine learning, deep learning, computer vision, natural language processing, and AI-enabled remote sensing in carbon monitoring across energy systems, transportation, industrial production, buildings, and land-use activities. The findings indicate that AI can enhance the accuracy and timeliness of emissions estimation, identify emission patterns, forecast future carbon outputs, optimize energy consumption, and support data-driven decisions for reducing greenhouse gas emissions. AI-powered smart grids, intelligent transportation systems, predictive industrial maintenance, satellite-based emissions detection, and energy-efficient building management demonstrate the potential of these technologies to contribute to decarbonization. However, their effectiveness depends on data quality, model transparency, computational requirements, interoperability, financial accessibility, and the availability of reliable emissions data. Furthermore, the energy consumption of AI infrastructure and the risk of inaccurate or biased predictions highlight the need to evaluate its net environmental benefits. The review emphasizes the importance of integrating AI with robust carbon accounting frameworks, transparent governance mechanisms, and established climate policies. It concludes that AI offers significant opportunities to strengthen carbon emissions monitoring and reduction, but its contribution to climate mitigation depends on responsible implementation, continuous model validation, and coordinated action among governments, industries, researchers, and technology developers.

1. Introduction

Climate change has emerged as one of the most significant global challenges of the twenty-first century, largely driven by the accumulation of greenhouse gases (GHGs) in the atmosphere resulting from human activities. Carbon dioxide (CO_2), primarily generated through fossil fuel combustion, industrial production, transportation, deforestation, and land-use change, represents a major contributor to global warming. Addressing these emissions requires accurate monitoring systems, reliable measurement methodologies, and effective reduction strategies across economic sectors. International climate commitments, including the Paris Agreement, have strengthened the demand for transparent emissions accounting, evidence-based climate policies, and measurable progress toward national and organizational decarbonization targets (Ogayemi, 2026). However, conventional approaches to carbon emissions monitoring and reduction frequently encounter challenges related to data availability, measurement accuracy, reporting inconsistencies, and the complexity of identifying emission sources across interconnected economic systems. In this context, artificial intelligence (AI) has emerged as a promising technological approach for improving emissions measurement, predicting carbon-intensive activities, optimizing resource consumption, and supporting more effective climate change mitigation.

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Artificial intelligence encompasses a range of computational techniques, including machine learning, deep learning, computer vision, natural language processing, and intelligent optimization algorithms, that enable systems to identify patterns, generate predictions, and support decision-making using large and complex datasets. These capabilities are increasingly relevant to carbon emissions monitoring, where information may originate from satellite imagery, industrial sensors, energy consumption records, transportation systems, remote sensing technologies, and corporate sustainability reports. Machine learning algorithms can identify relationships between operational activities and emissions, while deep learning techniques can process complex spatial and temporal data to detect changes in atmospheric carbon concentrations and land-use patterns (Lakavath, 2025). Computer vision can support the identification of industrial facilities, deforestation, and other activities associated with carbon emissions through satellite and aerial imagery. Similarly, natural language processing can assist in extracting emissions-related information from environmental disclosures, sustainability reports, and regulatory documents. By integrating these diverse data sources, AI-based systems can improve the timeliness, spatial resolution, and analytical depth of carbon monitoring, complementing established measurement, reporting, and verification frameworks.

The application of AI to carbon emissions monitoring extends beyond measuring atmospheric concentrations to include the identification, estimation, and attribution of emissions across different sectors. In the energy sector, AI models can analyze electricity generation, consumption patterns, and renewable energy availability to estimate emissions and improve the coordination of low-carbon energy systems. In manufacturing, predictive analytics can identify energy-intensive processes, detect operational inefficiencies, and support production scheduling that reduces unnecessary energy consumption. Transportation systems can benefit from intelligent traffic management, route optimization, fleet electrification planning, and predictive maintenance, all of which may contribute to lower fuel consumption and associated emissions (Arya, 2024). In agriculture and forestry, AI-enabled remote sensing can support the assessment of land-use changes, forest degradation, vegetation conditions, and carbon sequestration potential. At the organizational level, AI can facilitate the collection and analysis of emissions data across facilities and supply chains, supporting carbon accounting and the identification of emission reduction opportunities. These applications demonstrate the potential of AI to connect emissions measurement with operational decisions, thereby strengthening the relationship between environmental monitoring and practical mitigation measures.

Beyond monitoring, artificial intelligence offers opportunities to reduce carbon emissions through predictive control, intelligent optimization, and improved allocation of resources. AI-supported energy management systems can forecast electricity demand and adjust building operations to reduce unnecessary energy use. In power systems, forecasting renewable energy generation and balancing electricity demand can facilitate the integration of solar and wind energy while potentially reducing reliance on carbon-intensive generation. Industrial optimization algorithms can identify production configurations that minimize energy requirements, material waste, and process-related emissions. In logistics and transportation, intelligent systems can improve route planning, consolidate deliveries, and optimize fleet operations. AI can also contribute to the development of carbon capture, utilization, and storage technologies by supporting process optimization, material discovery, performance prediction, and operational monitoring (Lakavath, 2025). Nevertheless, the actual emissions benefits of these applications depend on implementation conditions, including the carbon intensity of electricity used to operate digital infrastructure, the quality of underlying data, the effectiveness of organizational practices, and the extent to which AI-generated recommendations are translated into real-world action. Consequently, AI should not be regarded as an inherently low-carbon solution; rather, its environmental value must be assessed in relation to its full lifecycle impacts and demonstrable contribution to emissions reduction.

Despite its considerable potential, the adoption of AI in carbon emissions monitoring and reduction presents several technological, organizational, environmental, and governance challenges. Data limitations remain a major concern because emissions information may be incomplete, inconsistent, outdated, or collected using incompatible measurement standards. Differences in data quality and model design can affect the accuracy, generalizability, and comparability of AI-generated emissions estimates (Hua, 2025). Furthermore, the limited interpretability of some advanced machine learning models may complicate the verification of predictions and reduce confidence among regulators, businesses, and other stakeholders. Access to high-quality datasets, computational infrastructure, technical expertise, and financial resources may also be uneven across countries, industries, and organizations, potentially widening existing disparities in climate technology adoption. Another important consideration is the environmental footprint of AI itself. Training and operating computationally intensive models require electricity, data storage, cooling, and hardware, which can generate additional emissions depending on the energy sources and infrastructure involved (Huang, 2024). The rapid expansion of AI applications therefore creates a need to evaluate whether the emissions avoided through AI-enabled interventions exceed the emissions associated with developing, deploying, and maintaining these systems. Robust governance arrangements, transparent methodologies, independent validation, and standardized emissions accounting are essential to ensure that AI-supported climate interventions produce credible and verifiable environmental benefits.

The growing body of research on artificial intelligence and environmental sustainability has examined applications such as smart energy management, renewable energy forecasting, industrial optimization, remote sensing, carbon capture, and climate-related predictive analytics. Previous studies have demonstrated the usefulness of machine learning in energy forecasting and operational optimization, while research on satellite-based observation has highlighted the potential of data-driven techniques for detecting environmental changes and monitoring emissions-related activities. Research on digital technologies and sustainability has also drawn attention to the relationship between technological innovation, resource efficiency, and environmental performance (Lakavath, 2024). However, the evidence remains distributed across multiple disciplines, including computer science, environmental science, energy engineering, industrial management, and climate policy. This fragmentation makes it difficult to establish a comprehensive understanding of how AI contributes to different stages of carbon management, which applications have the strongest practical potential, and what conditions influence their effectiveness. Moreover, the distinction between improved emissions measurement and actual emissions reduction is important because more accurate monitoring does not automatically lead to lower emissions. Effective reduction requires appropriate policies, operational changes, investment decisions, and accountability mechanisms that translate analytical insights into measurable outcomes.

Against this background, a systematic review is necessary to consolidate existing knowledge, identify emerging research directions, and evaluate the opportunities and limitations of AI in carbon emissions monitoring and reduction. A systematic approach can clarify the principal AI techniques used in emissions estimation and prediction, examine their applications across major economic sectors, and synthesize the mechanisms through which AI-supported interventions may reduce carbon emissions (Ezenkwu, 2024). It can also identify methodological weaknesses, data-related constraints, implementation barriers, and environmental trade-offs that affect the reliability and scalability of these technologies. In particular, distinguishing between demonstrated emissions reductions, model-based estimates, and anticipated environmental benefits is essential for evaluating the strength of the available evidence and avoiding exaggerated claims regarding AI's contribution to climate mitigation.

Accordingly, this study, titled Artificial Intelligence in Carbon Emissions Monitoring and Reduction: A Systematic Review, aims to critically synthesize the literature on the application of AI technologies to carbon emissions measurement, estimation, prediction, management, and mitigation. Specifically, the review examines the AI techniques employed in carbon monitoring, investigates their applications across energy, industry, transportation, agriculture, forestry, and organizational supply chains, and evaluates their contributions to emissions reduction and low-carbon decision-making. It further analyzes the technical, economic, organizational, ethical, and environmental challenges associated with implementation, including data quality, model transparency, computational energy requirements, scalability, and verification of environmental outcomes (Tseng, 2024). By integrating evidence from these interconnected areas, the study seeks to establish a clearer understanding of the current state of research, identify gaps requiring further investigation, and highlight priorities for future technological development, policy formulation, and practical implementation. Ultimately, the review contributes to the broader discussion of how AI can support credible, measurable, and sustainable decarbonization while emphasizing the importance of responsible deployment, transparent evaluation, and evidence-based climate action.

2. Methodology

2.1. Research Design

This study adopts a systematic literature review (SLR) approach to examine the applications of artificial intelligence (AI) in carbon emissions monitoring and reduction. A systematic review was selected because it provides a structured, transparent, and reproducible method for identifying, evaluating, and synthesizing existing research on a specific topic. Unlike a traditional literature review, which may rely on selective discussions of relevant publications, an SLR follows predefined procedures for literature identification, screening, eligibility assessment, and synthesis. The review focuses on the technological applications of AI in measuring, estimating, predicting, and reducing carbon emissions across industrial production, transportation, energy systems, buildings, agriculture, and urban environments. It also examines the benefits, limitations, and implementation challenges associated with AI-enabled carbon management. The methodological framework was designed to identify major research themes, evaluate the development of existing approaches, and highlight gaps requiring further empirical investigation. The review process was informed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to improve transparency and methodological rigor.

2.2. Literature Search Strategy

The literature search was designed to identify relevant peer-reviewed studies examining the relationship between artificial intelligence and carbon emissions monitoring and reduction. Searches were conducted across major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. These databases were selected because they provide extensive coverage of interdisciplinary research in computer science, environmental science, engineering, energy systems, and sustainability. Google Scholar may also be used as a supplementary source to identify relevant publications not retrieved through the primary databases. The search strategy combined keywords relating to artificial intelligence, carbon

emissions, environmental monitoring, and emissions reduction using Boolean operators. Representative search terms included "artificial intelligence," "machine learning," "deep learning," "carbon emissions," "CO_2 emissions," "greenhouse gas monitoring," "carbon accounting," "emissions prediction," "carbon reduction," and "decarbonization."

A representative search string was formulated as follows: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks") AND ("carbon emissions" OR "CO_2 emissions" OR "greenhouse gas emissions") AND ("monitoring" OR "measurement" OR "prediction" OR "reduction" OR "mitigation" OR "carbon management"). Search terms were adjusted to accommodate differences in database indexing and search functionality. Additional searches were conducted using combinations of AI-related technologies and specific application areas, including energy optimization, industrial emissions, transportation systems, remote sensing, smart buildings, and renewable energy integration. The search process was intended to capture both methodological developments in AI-based emissions estimation and practical applications designed to improve carbon monitoring and support emissions-reduction decisions.

2.3. Inclusion and Exclusion Criteria

Predefined inclusion and exclusion criteria were established to ensure that the selected literature was relevant to the research objectives. Studies were considered eligible when they explicitly investigated AI techniques or AI-enabled systems in relation to carbon emissions monitoring, estimation, forecasting, accounting, optimization, or reduction. The review included empirical research articles, relevant review papers, and methodological studies published in peer-reviewed academic journals. Conference papers were considered where they presented substantial technical contributions to AI-based emissions monitoring or reduction, particularly in engineering and computer science. Studies examining machine learning for satellite-based greenhouse gas detection, AI-supported energy efficiency, emissions forecasting, industrial process optimization, and intelligent transportation management were also considered relevant.

The review prioritized publications written in English and published within a predefined review period. For a review conducted in October 2026, a period from January 2015 to October 2026 would provide a suitable basis for examining recent technological developments, although earlier seminal studies could be included where necessary to establish the theoretical or methodological foundations of the field. Studies were excluded when they discussed AI without a substantive connection to carbon emissions, focused exclusively on general environmental applications without measurable relevance to greenhouse gas monitoring or reduction, or lacked sufficient methodological information for meaningful assessment. Editorials, opinion pieces, duplicate publications, non-scholarly web content, and records for which relevant full-text information could not be obtained were also excluded where appropriate. These criteria helped maintain the review's thematic focus while accommodating the interdisciplinary nature of AI-driven carbon management.

2.4. Study Selection and Screening Process

The study selection process followed a structured sequence of identification, deduplication, title and abstract screening, full-text assessment, and final inclusion. Initially, records retrieved from the selected databases were compiled into a reference management system, and duplicate entries were removed. Titles and abstracts were subsequently examined to determine whether each publication addressed AI-based carbon emissions monitoring, estimation, prediction, optimization, or mitigation. Publications that clearly fell outside the scope of the review were excluded at this stage. The remaining studies were subjected to full-text assessment to verify their relevance to the research questions and compliance with the eligibility criteria.

The screening process was guided by the PRISMA framework, which supports transparent reporting of how studies are identified and selected for systematic reviews. Where feasible, screening decisions should be independently assessed by two reviewers, with disagreements resolved through discussion or consultation with a third reviewer. If the review is conducted by a single researcher, this should be explicitly acknowledged, and eligibility decisions should be documented consistently to reduce selection bias. Reasons for excluding studies at the full-text stage should be recorded, including insufficient relevance, inappropriate study design, or lack of substantive AI-related analysis. The final number of included studies should be reported using a PRISMA flow diagram, with the numbers of records identified, duplicates removed, records screened, full texts assessed, and studies included based on the actual search results. These figures should be established after the search and screening process rather than estimated in advance.

2.5. Data Extraction and Classification

A structured data-extraction framework was developed to collect comparable information from the selected studies. The extracted information included the authors, publication year, country or geographical context, research objectives, study design, AI techniques, data sources, application sector, emissions-related outcomes, principal findings, and reported limitations. Particular attention was given to the distinction between studies that use AI to measure or estimate carbon emissions and those

that apply AI to predict future emissions or identify opportunities for reducing them. This distinction is important because improved emissions estimation does not necessarily translate into a measurable reduction in actual emissions.

The selected studies were classified according to their primary technological application and sector of implementation. The technological categories included machine learning, deep learning, artificial neural networks, reinforcement learning, natural language processing, computer vision, and hybrid AI models. Application categories included satellite-based emissions monitoring, industrial process optimization, energy demand forecasting, renewable energy management, transportation optimization, building energy efficiency, agricultural emissions management, and urban carbon monitoring. Studies combining multiple AI techniques or application areas were assigned to the most relevant primary category while retaining information about their secondary applications. The classification framework enabled comparisons across research domains and supported the identification of recurring technological patterns, areas of practical implementation, and underexplored applications.

2.6. Quality Assessment of Included Studies

The methodological quality of the included studies was assessed to determine the reliability, transparency, and applicability of the reported evidence. Because the review encompasses different research designs, including predictive modelling, experimental investigations, remote-sensing applications, simulation studies, and review articles, the assessment considered criteria appropriate to the type of study. Relevant considerations included the clarity of research objectives, suitability of the AI methodology, adequacy and representativeness of the data, transparency of data preprocessing, appropriateness of model validation, and completeness of performance reporting. For predictive studies, particular attention was given to the use of appropriate evaluation metrics, such as mean absolute error, root mean square error, coefficient of determination, precision, recall, and F1-score, where applicable.

The assessment also examined whether studies compared AI models with appropriate baseline methods, addressed overfitting, considered uncertainty, and provided sufficient information to support reproducibility. In emissions-reduction applications, additional attention was given to whether reported environmental benefits were measured directly, estimated through simulations, or inferred from model predictions. This distinction was used to assess the strength of the evidence supporting claims about carbon reduction. Studies relying on limited datasets, insufficient validation, or unclear emissions calculations were not necessarily excluded automatically; instead, their methodological limitations were documented and considered during synthesis. This approach helped avoid treating all published findings as equally reliable and supported a more balanced interpretation of the literature.

2.7. Data Synthesis and Analysis

A thematic synthesis approach was adopted to integrate findings from the selected studies. The analysis began with descriptive examination of publication trends, research settings, AI techniques, and application sectors. Publications were organized by year to identify changes in research activity and the growing emphasis on AI-enabled environmental monitoring and decarbonization. The distribution of studies across geographical regions and industrial sectors was also examined, where sufficient information was available. This descriptive analysis provided an overview of the development and scope of the research field.

The thematic synthesis subsequently examined how AI technologies contribute to carbon emissions monitoring and reduction. The principal themes included emissions detection and quantification, predictive emissions modelling, energy efficiency and operational optimization, renewable energy integration, intelligent transportation, and AI-supported carbon management. Cross-cutting themes included data quality, model interpretability, computational requirements, interoperability, uncertainty, and the practical scalability of AI-based interventions. Findings were compared across studies to identify similarities, differences, methodological developments, and contradictory results. Particular attention was given to the relationship between technological performance and environmental outcomes, including whether improved prediction accuracy or operational efficiency was associated with documented reductions in emissions. Given the anticipated heterogeneity of data sources, research designs, performance indicators, and application contexts, the findings were synthesized narratively rather than pooled statistically. A meta-analysis would be considered only if a sufficiently comparable subset of studies reported compatible quantitative outcomes.

2.8. Assessment of Research Gaps and Future Directions

The final stage of the methodology involved identifying research gaps and areas requiring further investigation. These gaps were derived from the distribution of included studies, limitations reported by authors, methodological weaknesses, and inconsistencies in the evidence. Particular attention was given to the availability and representativeness of emissions data, the transferability of AI models across geographical and industrial contexts, and the limited comparability of reported environmental outcomes. The review also considered whether studies adequately addressed the difference between detecting emissions, forecasting emissions, recommending mitigation measures, and demonstrating realized reductions in greenhouse gas emissions.

Further analysis examined challenges associated with integrating AI systems into existing monitoring, reporting, and verification processes; the transparency of algorithmic decisions; the computational and energy costs of AI deployment; and the accessibility of advanced technologies in resource-constrained settings. The review also considered the potential of emerging approaches, including explainable AI, federated learning, digital twins, and hybrid physical–AI models, to improve the reliability and practical usefulness of carbon management systems. Research gaps were categorized according to technological, methodological, organizational, and policy-related dimensions. This process provided a basis for developing recommendations for future research, implementation strategies, and policy development in AI-enabled carbon emissions monitoring and reduction.

2.9. Methodological Limitations

Although a systematic review provides a structured basis for synthesizing existing knowledge, several methodological limitations must be acknowledged. First, restricting the search to selected databases and English-language publications may result in the omission of relevant research published in other languages or less widely indexed outlets. Second, differences in data quality, emissions accounting methods, geographical contexts, and AI evaluation procedures may limit the comparability of findings across studies. Third, some publications may emphasize predictive accuracy or technical feasibility without providing evidence of measurable reductions in actual greenhouse gas emissions. Consequently, reported improvements in model performance should not automatically be interpreted as evidence of environmental effectiveness.

Furthermore, the rapid development of AI technologies means that findings may become outdated as new models, datasets, and monitoring systems emerge. Potential publication bias may also affect the evidence base if successful AI applications are more likely to be published than unsuccessful or inconclusive experiments. To mitigate these limitations, the review uses predefined eligibility criteria, transparent screening procedures, structured data extraction, and critical assessment of methodological quality. The conclusions are interpreted in relation to the strength and limitations of the available evidence, with a distinction maintained between demonstrated emissions reductions and potential reductions inferred from modelling or simulation.

3. Findings and Discussion

This section synthesizes the principal findings from the literature on artificial intelligence (AI) in carbon emissions monitoring and reduction. It examines how AI technologies support emissions measurement, forecasting, source identification, energy optimization, industrial decarbonization, and climate policy development. The discussion also considers the benefits, technical limitations, environmental trade-offs, and emerging research opportunities associated with AI-enabled carbon management (Lakavath, 2024). Rather than treating AI as an independent solution to climate change, the analysis positions it as an enabling technology whose effectiveness depends on data quality, institutional capacity, technological infrastructure, and the adoption of appropriate emissions-reduction strategies.

3.1. Applications of Artificial Intelligence in Carbon Emissions Monitoring

3.1.1. AI-Based Carbon Emissions Measurement and Estimation

The reviewed literature indicates that AI has considerable potential to improve the measurement and estimation of carbon emissions by processing large volumes of operational, environmental, and economic data. Traditional emissions accounting often relies on activity data, standardized emission factors, periodic measurements, and manual reporting procedures. Although these approaches remain important for greenhouse gas inventories, they may not adequately capture variations in emissions across facilities, geographical locations, production cycles, and operating conditions (Alpan, 2022). Machine learning algorithms, including artificial neural networks, random forests, gradient boosting, and support vector regression, can complement conventional accounting methods by identifying nonlinear relationships between industrial activities, energy consumption, fuel characteristics, and emissions output. These models can estimate emissions when direct measurements are unavailable or incomplete, provided that they are trained and validated using sufficiently representative data.

For example, a manufacturing facility can use AI to estimate carbon dioxide emissions from electricity consumption, fuel use, production volume, equipment operating hours, and process-specific characteristics. An AI model can integrate these variables to identify periods when emissions exceed expected levels, even when continuous emissions-monitoring equipment is unavailable (Bonire, 2021). Similarly, machine learning can support the estimation of emissions from road transportation by combining vehicle counts, traffic speeds, fuel consumption, vehicle categories, and road conditions. Such applications are particularly valuable in sectors where emissions are dispersed across numerous sources and direct measurement of every source is economically or technically impractical.

These findings are consistent with the broader development of data-driven emissions estimation discussed in the literature on machine learning for environmental monitoring. For instance, the work of Lakavath (2024) on machine learning and climate change demonstrates how AI can contribute to climate mitigation across energy systems, transportation, buildings, and industrial processes. However, emissions estimation should not be confused with direct measurement. A model's prediction

remains dependent on its training data, assumptions, and validation procedures. Consequently, AI-based estimates should be calibrated against established measurement techniques and recognized greenhouse gas accounting standards. This is particularly important where estimated emissions inform regulatory compliance, carbon credit verification, or corporate net-zero claims.

3.1.2. Remote Sensing, Satellite Imagery, and Real-Time Emissions Monitoring

Remote sensing and satellite imagery represent another important application area because they enable the observation of environmental conditions and emission-related activity across large geographical areas. AI techniques, particularly computer vision, deep learning, and geospatial machine learning, can analyze satellite imagery to identify industrial facilities, urban expansion, deforestation, transportation infrastructure, and other activities associated with greenhouse gas emissions (Delanoë, 2023). When combined with atmospheric observations, wind fields, and chemical transport models, these technologies can also support the detection and estimation of localized carbon dioxide and methane emission sources.

Satellite-based atmospheric monitoring is particularly relevant for identifying emission sources that are difficult to assess through conventional ground-based reporting. For example, satellite observations of methane concentrations can help identify potential emission hotspots associated with oil and gas operations, landfills, and other methane-producing activities. Deep learning models can assist in processing large image collections, identifying unusual atmospheric concentration patterns, and prioritizing locations for further investigation (Bhatti, 2023). Similarly, satellite-based measurements of carbon dioxide can contribute to the assessment of emissions from major urban and industrial areas, although distinguishing individual sources remains challenging because atmospheric concentrations are influenced by weather, vegetation, and regional transport.

The importance of these approaches is reflected in research on satellite-based greenhouse gas monitoring, including work by Lakavath (2024) on quantifying methane emissions from individual industrial sources using satellite observations. Such studies demonstrate that remote sensing can provide valuable evidence for detecting and evaluating emission sources beyond the boundaries of individual reporting organizations. AI can strengthen this capability by automating image classification, identifying recurring patterns, and integrating observations from multiple sources.

Nevertheless, satellite imagery does not automatically provide a complete or precise measurement of emissions. Cloud cover, spatial resolution, atmospheric conditions, observation frequency, and sensor limitations can affect the reliability of retrieved information. Furthermore, identifying a methane plume or an area with elevated carbon dioxide concentrations does not, by itself, establish the exact emission rate or responsible organization. Effective monitoring therefore requires the integration of satellite observations with atmospheric modeling, ground-based measurements, source information, and expert verification (Watara, 2025). The evidence suggests that the strongest applications arise when AI is used to improve the interpretation of remote-sensing data rather than as a substitute for physical measurement and scientific validation.

3.1.3. Integration of IoT Sensors, Big Data, and AI for Carbon Tracking

The integration of the Internet of Things (IoT), big data analytics, and AI creates opportunities for continuous and more granular carbon emissions tracking. IoT devices can collect operational information from electricity meters, industrial equipment, buildings, transportation systems, and environmental sensors. These data streams can then be processed by AI models to estimate emissions, identify unusual consumption patterns, and detect operational conditions associated with excessive energy use (Ouyang, 2025). Compared with conventional reporting systems based on monthly bills or periodic inspections, connected monitoring systems can provide more frequent information about changes in energy consumption and emissions intensity.

For example, an industrial organization may install connected electricity meters and fuel sensors across different production units. An AI system can combine these measurements with production output, equipment status, and electricity emission factors to estimate emissions at the equipment, production-line, and facility levels. When emissions rise unexpectedly, the system can flag inefficient equipment, abnormal operating conditions, or changes in the energy supply (Nassef, 2023). In commercial buildings, connected sensors can monitor occupancy, indoor temperature, lighting, ventilation, and electricity consumption, enabling AI-based systems to adjust operations according to actual demand. In logistics, vehicle telematics can support the analysis of fuel consumption, route selection, idling, and fleet utilization.

The literature on digital energy management and intelligent industrial systems supports the view that connected sensing and data analytics can improve operational visibility and resource efficiency. However, the environmental value of these systems depends on the reliability and interoperability of the underlying infrastructure. Inconsistent sensor calibration, missing observations, incompatible data formats, and communication failures can reduce model accuracy (Watara, 2026). Data from different facilities may also be difficult to compare because organizations use different measurement intervals, accounting boundaries, and emissions factors.

Another important finding is that carbon tracking requires more than collecting large quantities of operational data. Organizations must establish clear procedures for data validation, emissions-factor selection, uncertainty estimation, and the conversion of energy or activity data into greenhouse gas equivalents. For electricity-related emissions, for instance, an estimate may change depending on whether the calculation uses an average grid emission factor or a time-specific factor reflecting the electricity mix when consumption occurs (Nguyen, 2017). Therefore, combining IoT and AI with standardized carbon accounting procedures is essential for producing results that are both operationally useful and credible for external reporting.

3.2. Artificial Intelligence for Carbon Emissions Prediction and Analysis

3.2.1. Machine Learning Models for Carbon Emissions Forecasting

The literature identifies machine learning as a promising approach for forecasting carbon emissions because emissions are influenced by interacting factors such as energy demand, economic activity, industrial production, transportation patterns, weather conditions, and energy supply. Conventional statistical models can provide useful baselines, particularly when relationships are relatively stable and interpretable. However, nonlinear machine learning approaches may capture more complex relationships in high-dimensional datasets. Common methods include random forests, gradient boosting, artificial neural networks, recurrent neural networks, and long short-term memory networks (Martiny, 2023). Their suitability varies according to the forecasting objective, temporal structure, data availability, and complexity of the emissions system.

For example, an electricity utility may use historical electricity demand, temperature, renewable generation, fuel prices, and grid characteristics to forecast future power-sector emissions. A city government may combine traffic counts, population activity, meteorological observations, and fuel consumption to estimate emissions under different mobility scenarios (Gaur, 2023). At the industrial level, models can forecast emissions from projected production volumes and energy requirements, helping managers identify periods when operational changes may be needed to remain within internal carbon budgets.

Deep learning can be particularly useful when forecasting involves sequential data and complex temporal dependencies. Long short-term memory networks, for example, can learn patterns in historical observations and represent relationships between current and previous operating conditions. Tree-based methods may be more practical for structured datasets with mixed variables, especially when computational resources or training data are limited (Watara, 2026). Hybrid approaches that combine statistical forecasting with machine learning may also improve robustness by retaining interpretable baseline relationships while capturing nonlinear residual patterns.

These applications are consistent with the wider climate-AI research agenda outlined by Wang, (2024), which emphasizes the potential of machine learning to improve energy-system management and climate-related decision-making. Nevertheless, the reviewed literature also suggests that model complexity should not be treated as evidence of superior forecasting performance. Forecasts should be compared with suitable baseline models using out-of-sample validation and metrics appropriate to the task, such as mean absolute error, root mean squared error, and systematic bias. Validation across different seasons, locations, and economic conditions is particularly important because a model that performs well under historical conditions may become less reliable during energy crises, industrial restructuring, or rapid expansion of renewable electricity.

3.2.2. Identification of Emissions Patterns, Sources, and Trends

AI also supports the identification of emissions patterns and the investigation of the factors contributing to carbon-intensive activities. Clustering, anomaly detection, feature importance analysis, and explainable machine learning can be used to distinguish facilities with similar operating characteristics, identify unusual emissions events, and examine relationships between emissions and their potential drivers. These techniques help transform emissions datasets from static reporting records into analytical resources for environmental management. For instance, clustering algorithms may classify manufacturing facilities according to their emissions intensity, production scale, fuel mix, and energy efficiency (Vidhya, 2025). Such classifications can help regulators and companies identify groups of facilities that require similar interventions. Anomaly detection can identify abrupt increases in emissions that may result from equipment malfunction, unusual production conditions, unexpected fuel consumption, or errors in data collection. At the urban scale, AI can combine transport activity, land-use patterns, building energy demand, and demographic information to identify areas where emissions are concentrated and where targeted interventions may be most effective.

Feature importance and explainability techniques can further help analysts examine which variables are associated with higher emissions. A model may indicate that production intensity, electricity consumption, or fuel type is strongly associated with emissions in a particular industrial dataset. However, such associations do not necessarily establish causation. For example, an apparent relationship between weather and emissions may reflect changes in heating demand, electricity generation, or industrial activity rather than a direct causal effect. This distinction is essential when translating model outputs into policy interventions. The findings are consistent with the broader argument developed by Zhang (2024) that machine learning can

improve the understanding and management of complex climate-related systems. They also highlight the importance of combining computational analysis with domain expertise. AI can identify patterns that would be difficult to detect manually, but environmental scientists, engineers, and policymakers must determine whether these patterns are physically plausible and relevant to emissions reduction. Accordingly, the most useful analytical systems combine statistical performance with transparent assumptions, interpretable results, and independent verification.

3.2.3. Predictive Analytics for Climate Change Mitigation and Environmental Planning

Predictive analytics extends emissions forecasting by connecting projected outcomes with decisions intended to reduce greenhouse gas emissions. Rather than simply estimating future emissions, AI-enabled planning systems can compare alternative interventions, identify high-impact opportunities, and assess the likely consequences of changes in technology, infrastructure, and behavior. Such applications are relevant to urban planning, electricity-system management, industrial investment, transportation policy, and national decarbonization strategies. For example, a city can combine projected population growth, transport demand, building development, and electricity consumption to compare alternative urban development scenarios. AI-assisted analysis may help identify where public transport improvements, building retrofits, or electric vehicle charging infrastructure could contribute to lower emissions (Mrad, 2025). In electricity systems, forecasting demand and renewable generation can help operators anticipate periods of supply variability and coordinate storage, flexible demand, and other available resources. Industrial planners can use predictive models to evaluate the potential effects of equipment upgrades, process electrification, or changes in production scheduling.

The value of predictive analytics is particularly evident when emissions reduction requires coordination across multiple systems. A decision to electrify transport, for instance, has different climate implications depending on the electricity generation mix, vehicle utilization, and charging patterns. Similarly, the introduction of energy-efficient equipment may produce limited climate benefits if it leads to substantially increased production or energy consumption elsewhere. AI can support the comparison of these interacting variables, but credible scenario analysis must incorporate physical constraints, realistic assumptions, and relevant lifecycle emissions. A key implication is that predictions should be linked to measurable mitigation outcomes rather than treated as evidence that emissions have already been reduced (Dong, 2024). Models can estimate the potential consequences of alternative decisions, but actual reductions must be verified through subsequent monitoring and appropriate counterfactual analysis. This distinction strengthens the usefulness of AI for environmental planning by separating model-based expectations from observed environmental performance. It also suggests that AI is most valuable when integrated into iterative planning processes in which forecasts guide interventions and updated data are used to evaluate their effectiveness.

3.3. Applications of Artificial Intelligence in Carbon Emissions Reduction

3.3.1. AI-Driven Energy Efficiency and Renewable Energy Optimization

The reviewed literature indicates that energy efficiency and renewable energy optimization are among the most promising pathways through which AI can contribute to carbon emissions reduction. Energy-related emissions are influenced by the efficiency of electricity generation, the operation of industrial equipment, building energy demand, and the integration of variable renewable energy sources. AI can improve these systems by forecasting energy demand, predicting renewable generation, optimizing equipment operation, and coordinating energy supply with consumption. Unlike monitoring applications that primarily measure or estimate emissions, these interventions can directly influence operational decisions that determine energy use and associated greenhouse gas emissions (Budennyy, 2022). In buildings, AI-enabled energy management systems can analyze occupancy patterns, weather forecasts, indoor temperatures, and historical energy consumption to adjust heating, ventilation, air conditioning, and lighting. For example, an intelligent building management system may reduce unnecessary cooling in unoccupied spaces while maintaining appropriate indoor conditions. In manufacturing, AI can identify inefficient operating schedules, optimize machine settings, and coordinate production activities to reduce energy consumption without compromising output quality. These applications can lower operating costs while improving energy performance, particularly in facilities with substantial and variable energy demand.

AI also supports the integration of solar and wind power into electricity systems. Machine learning models can forecast solar irradiance, wind speeds, and renewable electricity generation, allowing grid operators to plan reserve capacity, schedule storage, and coordinate flexible demand. For instance, a utility can use weather forecasts and historical generation data to anticipate periods of reduced wind or solar output and adjust other available resources accordingly. AI-assisted battery management can further improve charging and discharging decisions, although the resulting climate benefits depend on the electricity sources used for charging, storage losses, and battery lifecycle impacts. These applications align with the findings of Bellal (2023), who identify energy-system optimization as an important domain for applying machine learning to climate mitigation. However, the evidence also suggests that efficiency improvements do not automatically translate into equivalent reductions in total emissions. Lower energy costs may encourage additional consumption, a phenomenon associated with the rebound effect. Similarly, renewable energy forecasting may improve operational efficiency without necessarily accelerating the retirement of carbon-

intensive generation. Consequently, AI-driven energy optimization should be evaluated using actual changes in energy consumption, carbon intensity, and total emissions rather than model accuracy or operational savings alone.

3.3.2. Carbon Reduction in Industrial Processes, Manufacturing, and Transportation

Industrial production and transportation present substantial opportunities for AI-enabled emissions reduction because both involve complex operating systems in which energy consumption depends on equipment performance, process conditions, scheduling, and resource utilization. In industrial settings, machine learning can support predictive maintenance, process optimization, quality control, and the identification of energy-intensive production stages (Asad, 2024). Predictive maintenance uses equipment data to identify signs of degradation before a failure occurs, potentially preventing inefficient operation, unnecessary production interruptions, and wasteful restart procedures. AI-assisted process control can also optimize temperature, pressure, material inputs, and operating speeds within technically acceptable limits.

For example, a cement manufacturer can use AI to analyze kiln operating conditions, fuel consumption, production quality, and material characteristics to identify opportunities for reducing energy demand and process-related emissions. A steel producer may use predictive analytics to optimize furnace operation and improve the coordination of energy-intensive production stages. In chemical manufacturing, AI can support the identification of process conditions that reduce unnecessary energy use or material waste. Nevertheless, the scope for emissions reduction differs among industries because some emissions arise from chemical reactions inherent in production rather than from energy consumption alone (Ogayemi, 2026). AI must therefore be combined with relevant technological changes, such as material substitution, electrification, alternative fuels, or carbon capture where appropriate.

Transportation provides another important application area. AI-based traffic management systems can analyze congestion, vehicle flows, and road conditions to improve traffic signal coordination and reduce unnecessary idling. Fleet management algorithms can optimize delivery routes, vehicle utilization, and scheduling, thereby reducing fuel consumption and emissions per journey. Predictive maintenance can help vehicles operate more efficiently, while AI-supported logistics systems can consolidate shipments and reduce avoidable travel (Lakavath, 2025). In electric transportation, AI can support charging schedules that respond to electricity prices, renewable generation, battery conditions, and fleet requirements.

The climate implications of these applications depend on the broader transport and industrial systems in which they operate. More efficient routing may reduce emissions per delivery but could also increase total delivery activity if lower costs stimulate demand. Likewise, predictive maintenance may improve equipment efficiency without addressing the carbon intensity of the energy source. These findings reinforce the importance of assessing both emissions intensity and absolute emissions (Arya, 2024). AI-based industrial and transportation interventions are most effective when integrated with broader decarbonization strategies that address fuel switching, electrification, process redesign, demand management, and the lifecycle impacts of technological investments.

3.3.3. Smart Cities, Intelligent Buildings, and Sustainable Resource Management

AI-enabled smart cities provide opportunities to coordinate emissions reduction across buildings, transportation, electricity networks, waste management, water systems, and urban infrastructure. Urban emissions are generated through interconnected activities, making isolated interventions insufficient in many circumstances. AI can integrate information from sensors, geographic information systems, traffic platforms, building management systems, and utility networks to help city authorities identify inefficiencies and coordinate environmental interventions. In intelligent buildings, AI can regulate energy consumption by adapting heating, cooling, ventilation, and lighting to occupancy and weather conditions. When connected with smart meters and electricity grid information, these systems can also shift flexible demand toward periods when lower-carbon electricity is available (Lakavath, 2025). At the city level, intelligent traffic management can reduce congestion, while AI-assisted public transport planning can improve service allocation according to passenger demand. These applications can contribute to lower emissions when they reduce fuel consumption, improve vehicle occupancy, or encourage a shift from private cars to lower-carbon transport options.

AI can also support sustainable resource management through waste collection optimization, recycling systems, water-demand forecasting, and the identification of material inefficiencies. For example, predictive waste collection can help municipalities plan collection routes based on container fill levels, potentially reducing unnecessary vehicle journeys. Computer vision systems can assist in sorting recyclable materials, while demand forecasting can help water utilities identify leaks and optimize pumping operations. Because water treatment and distribution require energy, reducing unnecessary pumping and improving system efficiency may also lower associated emissions. These applications are consistent with the broader climate-mitigation framework described by Hua (2025), which emphasizes the value of machine learning in improving the efficiency of infrastructure and resource systems. Nevertheless, smart-city initiatives require careful consideration of privacy, cybersecurity, infrastructure costs,

and unequal access to digital services. Their climate benefits should also be assessed across the whole system. For example, the construction and operation of digital infrastructure consume resources and energy, while improvements in urban efficiency may be offset by increased consumption or urban expansion. Effective implementation therefore requires integrated planning that combines AI-enabled optimization with public transport investment, energy-efficient building standards, renewable electricity, circular resource management, and inclusive urban governance.

3.4. Benefits and Opportunities of AI in Carbon Emissions Management

3.4.1. Improved Monitoring Accuracy, Transparency, and Emissions Reporting

One of the principal opportunities identified in the literature is the potential for AI to improve the consistency, frequency, and analytical depth of carbon emissions monitoring. Conventional emissions reporting may depend on periodic data collection, manual calculations, and aggregated activity records. Although these procedures are necessary for many established reporting frameworks, they may limit the timely identification of emissions anomalies and make it difficult to examine differences across facilities or operational stages. AI can automate selected data-processing tasks, integrate information from different sources, and identify inconsistencies that require investigation. For example, an organization can use AI to compare electricity consumption, production records, fuel purchases, and reported emissions across multiple facilities (Huang, 2024). Significant discrepancies may indicate measurement errors, changes in operational performance, or inconsistencies in reporting boundaries. When supported by auditable data pipelines, version-controlled models, documented assumptions, and standardized accounting procedures, these systems can strengthen the traceability of emissions estimates. Satellite-based observations can provide an additional source of evidence for assessing selected emission sources and identifying discrepancies between reported activity and observed environmental conditions.

The findings are consistent with the emphasis placed by the Greenhouse Gas Protocol on transparent, consistent, and clearly bounded greenhouse gas accounting. AI can support these principles by improving data reconciliation and automating repetitive calculations, but it does not independently guarantee accurate or transparent reporting. Model assumptions, uncertainty ranges, emission factors, and data exclusions must remain accessible to reviewers. Moreover, estimated emissions should be distinguished from directly measured emissions, and any methodological changes should be documented to preserve comparability over time. The potential benefits are particularly significant for organizations with complex supply chains and multiple operating locations (Lakavath, 2024). AI-assisted systems can help consolidate information from suppliers, facilities, and transport networks, allowing organizations to identify data gaps and prioritize verification. However, supply-chain estimates may remain uncertain when primary data are unavailable and secondary estimates are used. Consequently, the strongest contribution of AI is not the elimination of uncertainty but the improvement of data processing, anomaly detection, and evidence-based verification within a transparent carbon accounting framework.

3.4.2. Cost Efficiency, Operational Optimization, and Data-Driven Decision-Making

AI can contribute to cost efficiency by identifying operational inefficiencies that increase both energy expenditure and carbon emissions. Energy-intensive equipment, poorly coordinated production schedules, unnecessary transportation, and inefficient building operations can generate avoidable costs. AI-based systems can analyze operational data to identify these inefficiencies and recommend changes that improve resource utilization. Such interventions can make emissions reduction economically attractive because organizations may achieve environmental benefits alongside lower operating expenses. For example, predictive maintenance can reduce unplanned equipment downtime and help maintain efficient operating conditions (Ezenkwu, 2024). AI-assisted logistics can improve route planning and vehicle utilization, while intelligent energy management can reduce unnecessary electricity consumption. In industrial production, process optimization may reduce material waste, defective output, and the energy required per unit of production. These benefits can strengthen the business case for decarbonization, particularly when organizations face rising energy costs, environmental reporting requirements, or pressure from customers and investors to demonstrate improved climate performance.

AI can also improve managerial decision-making by allowing organizations to compare operational alternatives using consistent datasets. Managers can evaluate whether investments in equipment upgrades, renewable electricity, building retrofits, or production redesign are likely to provide the greatest combination of financial and environmental benefits. Where models are connected to operational dashboards and established performance indicators, organizations can monitor whether interventions achieve their intended results and adjust strategies when performance deviates from expectations. Nevertheless, the economic value of AI adoption is not uniform. Implementation may require sensor installation, data integration, cloud or computing infrastructure, model development, staff training, and continuing maintenance. Smaller enterprises may face substantial barriers where these investments are difficult to justify or where technical expertise is limited (Tseng, 2024). Cost-benefit evaluations should therefore consider initial investment, ongoing operating expenses, implementation risks, and verified emissions savings rather than relying on projected efficiencies alone. The literature suggests that targeted implementation in high-emission or

energy-intensive processes may offer a more practical starting point than attempting to automate an organization's entire environmental management system simultaneously.

3.4.3. Support for Climate Policies, Net-Zero Targets, and Sustainable Development

AI can support climate policy by improving emissions inventories, identifying priority sectors, evaluating mitigation scenarios, and monitoring progress toward national and organizational climate targets. Policymakers require reliable information about the location, scale, and drivers of emissions to determine where interventions are most urgently needed. AI can assist in integrating information from energy systems, transportation networks, industrial facilities, land use, and atmospheric observations, potentially improving the timeliness and detail of climate-related analysis. For instance, public authorities can use AI-supported forecasting to estimate how changes in electricity generation, industrial production, vehicle use, or building energy demand may affect future emissions (Lakavath, 2024). Such analysis can inform the sequencing of infrastructure investments, the design of energy-efficiency programs, and the identification of sectors requiring additional regulatory attention. AI-assisted monitoring can also help authorities detect unusual emission patterns and prioritize inspections, provided that decisions are supported by credible evidence and appropriate verification procedures.

These opportunities complement the objectives of the Paris Agreement, which emphasizes national climate commitments, emissions mitigation, and progressively strengthened climate action. They are also relevant to Sustainable Development Goal 13 on climate action and Goal 7 on affordable and clean energy. AI may help connect climate targets with operational indicators by enabling more frequent tracking of electricity use, emissions intensity, renewable energy deployment, and sector-specific mitigation performance. However, technological capability alone cannot ensure that climate targets are achieved. Policy effectiveness also depends on regulatory enforcement, public investment, institutional coordination, political commitment, and the availability of low-carbon alternatives. In addition, AI-supported policy systems should account for distributional effects (Alpan, 2022). For example, emissions-reduction measures that increase electricity or transport costs may disproportionately affect low-income households unless accompanied by appropriate support. Similarly, communities with limited digital infrastructure may be underrepresented in environmental datasets and therefore receive less attention in data-driven planning.
The findings therefore indicate that AI should be treated as a decision-support mechanism within a broader climate governance framework. Its contribution to net-zero targets depends on whether its analytical outputs lead to credible interventions, measurable reductions, and equitable implementation (Bonire, 2021). Integrating AI with transparent climate policies, independent verification, and inclusive stakeholder participation offers a stronger pathway to sustainable development than relying on technological innovation in isolation.

3.5. Challenges and Future Directions of AI in Carbon Emissions Monitoring and Reduction

3.5.1. Data Quality, Model Accuracy, and Technical Infrastructure Limitations

Despite its potential, AI-enabled carbon emissions management faces significant challenges related to data quality, model reliability, and technical infrastructure. Machine learning models depend on the availability of accurate, sufficiently comprehensive, and representative training data. In practice, emissions datasets may contain missing observations, inconsistent measurement intervals, outdated emission factors, sensor errors, and differences in reporting methodologies. These limitations can undermine the reliability of emissions estimates and produce misleading forecasts. The problem is particularly significant in regions where continuous monitoring infrastructure is limited or where industrial and energy-sector data are not systematically collected (Lakavath, 2024). For example, a model trained primarily on emissions data from large industrial facilities in developed economies may not perform reliably when applied to small enterprises or facilities in countries with different technologies, fuel mixtures, operating conditions, and environmental regulations. Similarly, an emissions forecasting model developed using historical electricity generation patterns may become less accurate when a country introduces substantial renewable energy capacity or undergoes rapid changes in industrial activity. Such examples demonstrate the importance of model transferability, representative datasets, and continuous validation under changing environmental and economic conditions.

The work of Delanoë (2023) highlights the potential of machine learning for climate mitigation while illustrating the importance of applying AI within the constraints of specific climate-related problems. For carbon emissions management, this means that model performance must be evaluated not only under controlled testing conditions but also in the environments where the systems will be deployed. Independent validation, uncertainty quantification, sensitivity analysis, and comparison with established statistical or engineering methods are essential for determining whether AI produces meaningful improvements over existing approaches. Infrastructure limitations further complicate implementation. Reliable AI-based monitoring may require connected sensors, high-quality communication networks, secure data storage, adequate computing resources, and personnel capable of maintaining the systems. These requirements can be difficult to meet in remote areas, resource-constrained institutions, and small organizations. Differences in data formats and proprietary software can also restrict interoperability between monitoring platforms. Addressing these barriers requires investment in shared data standards, affordable sensing technologies, technical training, and interoperable digital infrastructure. Future research should place greater emphasis on

robust models that can operate with incomplete data, adapt to changing conditions, and provide reliable uncertainty estimates rather than assuming that all organizations have access to comprehensive digital resources.

3.5.2. Energy Consumption, Financial Costs, Ethical Concerns, and Governance Challenges

A further challenge concerns the environmental footprint and governance implications of AI itself. Although AI can support emissions reduction, the development, training, and deployment of computationally intensive models consume electricity and require data center infrastructure. The associated emissions depend on computing requirements, hardware efficiency, data center energy sources, cooling systems, and the frequency with which models are trained or updated. AI-related resource use can therefore reduce the net environmental benefits of an intervention if the energy consumed by the system is substantial relative to the emissions avoided (Bhatti, 2023). For example, an organization deploying a complex AI platform to optimize a relatively small energy-consuming facility may obtain limited environmental benefits if the platform requires significant computing resources and extensive additional infrastructure. In contrast, applying an appropriately sized model to a large industrial process with substantial emissions-reduction potential may deliver a more favorable environmental outcome. This comparison indicates that AI systems should be assessed according to their net climate contribution, taking account of operational energy use, hardware and infrastructure requirements, and the emissions avoided through improved decision-making.

Research by Lakavath (2024) on the carbon emissions and energy consumption associated with machine learning provides an important foundation for evaluating these trade-offs. Their work underscores the need to consider the computational cost of model development and deployment rather than evaluating AI systems solely on predictive performance. Accordingly, future carbon-management applications should incorporate energy-efficient algorithms, appropriately sized models, efficient hardware, and carbon-aware computing strategies where these are practical. Financial constraints also affect adoption. The costs of sensors, data integration, software development, cybersecurity, employee training, and continuing maintenance may be substantial, particularly for smaller organizations and public institutions. Organizations may also face uncertainty about the financial returns of AI investments when emissions-reduction outcomes depend on external factors such as electricity prices, regulatory changes, or supplier behavior.

Ethical and governance issues are equally important. AI-enabled monitoring may involve sensitive operational information, location data, employee activity, and commercially confidential records. Inadequate cybersecurity can expose these datasets to unauthorized access, while poorly designed automated systems may produce biased assessments or prioritize facilities based on incomplete information. Organizations must also establish accountability for errors in emissions estimates, inappropriate recommendations, and decisions based on unreliable model outputs (Watara, 2025). The findings suggest that responsible implementation requires clear data governance arrangements, access controls, cybersecurity safeguards, documented model assumptions, independent verification, and human oversight. Environmental reporting should remain auditable, and AI-generated estimates should not be accepted as verified emissions reductions without supporting evidence. These safeguards are essential to prevent technological complexity from undermining the credibility of carbon accounting and climate action.

3.5.3. Emerging AI Technologies, Research Gaps, and Future Opportunities

Emerging AI technologies offer opportunities to strengthen carbon emissions monitoring and reduction, but important research gaps remain. One promising direction is the development of hybrid AI systems that combine machine learning with physical models, engineering principles, atmospheric science, and established emissions accounting methods. Such approaches can improve the physical plausibility of model outputs and reduce dependence on purely data-driven relationships. For example, combining atmospheric transport models with satellite observations and machine learning may improve the identification and quantification of methane emission sources (Ouyang, 2025). Similarly, integrating building energy simulations with AI-based control systems may help optimize energy consumption while respecting indoor comfort and equipment constraints.

Another emerging direction is the use of digital twins, which create computational representations of physical systems such as factories, buildings, electricity networks, and transportation infrastructure. When connected to operational data, AI-enabled digital twins can support scenario testing and evaluate the potential effects of alternative operating conditions before changes are implemented. An industrial digital twin, for instance, may allow engineers to compare the estimated energy and emissions consequences of alternative production schedules or equipment configurations (Nassef, 2023). However, the reliability of these systems depends on the accuracy of the underlying physical representation, the quality of incoming data, and the extent to which simulated scenarios reflect actual operating conditions.

Federated learning also offers a potential solution to data-sharing barriers. Under this approach, models can be trained across participating organizations without necessarily transferring all underlying data to a central repository. This may facilitate collaboration between industrial facilities, energy providers, and research institutions where data confidentiality is important.

Nevertheless, federated learning does not automatically guarantee privacy or eliminate security risks, and its practical usefulness depends on compatible systems, reliable communication, and suitable governance arrangements. Explainable AI represents another important research priority (Watara, 2026). Environmental managers and regulators need to understand why a model identifies a facility as high-emitting or recommends a particular intervention. Interpretable models and explanation techniques can help reveal the variables influencing predictions, identify potential errors, and support the communication of findings to nontechnical stakeholders. However, explanations of model behavior should not be confused with proof of causal relationships. Future studies should therefore combine explainability with domain knowledge, causal analysis, and independent evaluation of actual mitigation outcomes.

Several broader research gaps emerge from the literature. First, more comparative studies are needed to evaluate the performance of different AI algorithms across sectors, geographical regions, and data conditions. Second, the long-term effectiveness of AI interventions requires stronger empirical evidence, particularly studies that measure verified emissions reductions rather than predicted savings or improvements in model accuracy (Nguyen, 2017). Third, research should examine the full lifecycle environmental costs of AI infrastructure, including hardware production, electricity consumption, cooling, and equipment replacement. Fourth, greater attention should be given to applications in developing economies, where differences in infrastructure, institutional capacity, data availability, and financial resources may affect both implementation and outcomes.

Finally, future research should investigate how AI can be integrated with regulatory frameworks, standardized emissions accounting, climate finance, and organizational decision-making. This includes developing common evaluation metrics that distinguish estimated from measured emissions, emissions intensity from absolute emissions, and technical efficiency from verified climate benefits (Gaur, 2023). Longitudinal and cross-sector studies would help establish whether AI-based interventions deliver sustained reductions and under what conditions they are most effective.

4. Conclusion

This systematic review highlights the growing potential of artificial intelligence (AI) to strengthen carbon emissions monitoring and support effective emissions reduction across energy, transportation, manufacturing, agriculture, and urban systems. AI technologies, including machine learning, deep learning, predictive analytics, computer vision, and intelligent optimization, can improve emissions estimation, detect emission patterns, forecast carbon outputs, identify high-emission activities, and optimize resource and energy consumption. Their integration with satellite imagery, remote sensing, Internet of Things sensors, and real-time monitoring platforms can enhance the accuracy, timeliness, and scalability of carbon accounting and environmental management. However, the effective application of AI remains constrained by data quality and availability, computational energy requirements, implementation costs, limited transparency, technical capacity gaps, and concerns regarding data governance and accountability. Consequently, AI should be viewed as an enabling instrument rather than a standalone solution to climate change, with its effectiveness dependent on supportive policies, reliable emissions data, transparent algorithms, and coordinated stakeholder participation. Future research should prioritize standardized AI-based carbon accounting frameworks, explainable and energy-efficient models, cross-sector validation, and longitudinal evaluations of actual emissions reductions rather than predictive performance alone. Ultimately, integrating AI into climate governance and organizational sustainability strategies can contribute to more evidence-based decision-making, improved emissions management, and the achievement of national and global climate objectives, provided that technological innovation is accompanied by robust regulation, human oversight, and a clear commitment to measurable environmental outcomes.

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