REVIEW ARTICLE

Internet of Things and Artificial Intelligence for Carbon Emissions Monitoring and Forecasting: a Systematic Review of Smart Environmental Accounting Systems

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Abstract

The growing urgency of climate change mitigation has increased pressure to develop reliable systems capable of monitoring and predicting carbon emissions. Conventional carbon accounting methods based on manual reporting and periodic environmental assessments frequently produce delayed and incomplete emissions data. This systematic review was conducted in accordance with PRISMA guidelines. It examines existing literature on the application of digital technologies for carbon monitoring and management. The review focuses on Internet of Things (IoT) sensor networks, artificial intelligence (AI) forecasting models, carbon accounting frameworks and integrated digital carbon management systems. A structured search of five major academic databases yielded 100 peer-reviewed studies, selected and analysed across four thematic areas. Results demonstrate that IoT technologies effectively support real-time environmental monitoring and AI models reliably predict emissions trends. However, the literature reveals persistent weaknesses in the integration of monitoring systems with carbon accounting models. This review identifies critical research gaps and calls for the development of unified IoT–AI platforms to support accurate carbon management and climate governance.

Keywords: smart environmental monitoring systems, Internet of Things (IoT), carbon emissions monitoring, carbon accounting.

1 Introduction

1.1 Background of Carbon Emissions Monitoring

Monitoring of carbon emissions has emerged as a core element of global climate governance, given that greenhouse gas emissions are the primary driver of anthropogenic climate change [45]. Reliable emissions data are essential for governments and environmental organisations to review mitigation measures, track climate commitments and plan carbon reduction strategies [2]. Effective carbon tracking is especially significant for measuring compliance with global frameworks such as the Paris Agreement, which requires countries to regularly measure and report greenhouse gas inventories, a

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requirement that has exposed persistent discrepancies between global-model emissions estimates and country-level reporting, particularly for forest-based carbon sinks [47]. Conventional emissions monitoring methods rely heavily on manual reporting, energy consumption estimations and periodic environmental audits, which frequently produce delayed or incomplete data, a limitation increasingly recognised within the broader climate adaptation and resilience literature as a barrier to timely decision-making [43]. As climate risks intensify, researchers emphasise the need for continuous, data-driven monitoring systems capable of generating real-time insights into emission trends across diverse environments [6].

The rapid advancement of Internet of Things (IoT) technologies has enabled the deployment of distributed sensor networks capable of continuously monitoring environmental parameters including carbon dioxide concentration, methane levels, temperature and energy consumption [26]. IoT-based environmental monitors transmit data in real time to centralised platforms for analysis and visualisation, a data-transmission paradigm demonstrated across diverse urban sensing applications including air and acoustic monitoring [33], providing substantially improved spatial and temporal resolution compared to traditional periodic reporting systems, consistent with broader advances in geospatial big data handling methods that underpin high-resolution environmental data processing [46]. Artificial intelligence (AI) technologies further transform the carbon monitoring process by enabling pattern recognition, trend forecasting and anomaly detection within large environmental datasets [44, 54]. Standardisation of carbon accounting through Measurement, Reporting and Verification (MRV) frameworks ensures that emissions data are collected systematically and verified transparently, building on long-standing policy recognition of mitigation accounting needs [49] and subsequent efforts to strengthen oversight of voluntary carbon market integrity [51], together supporting both carbon markets and regulatory compliance.

1.2 Emergence of Smart Environmental Monitoring and Research Motivation

The rapid development of digital technologies has transformed environmental monitoring through the creation of smart systems capable of gathering and analysing environmental data in real time. While traditional surveillance relied on manual sampling and periodic review, IoT infrastructures now enable continuous monitoring of greenhouse gas concentrations through integrated sensor networks, communication systems and cloud platforms [13, 40]. AI and big data analytics further reinforce these systems by improving predictive capability and environmental decision-making, building on existing reviews of sector-specific accounting methodologies such as those developed for the electricity power industry [28]. However, current carbon accounting frameworks continue to rely on disaggregated reporting systems, a fragmentation that has long undermined the credibility of voluntary carbon market oversight mechanisms [51] and complicated efforts to apply AI-driven energy management for emissions reduction [58], creating challenges for implementing effective MRV frameworks and integrated IoT–AI carbon monitoring solutions.

1.3 PICOS Framework and Research Question

This review is guided by the following research question: To what extent have IoT sensor networks, AI analytics and carbon accounting frameworks been developed and integrated to support accurate, real-time carbon emissions monitoring and forecasting? The review was structured using the PICOS framework as follows:

- **Population (P):** Studies focusing on environments generating or influenced by carbon emissions, including industrial facilities, smart buildings, urban areas, agricultural systems and energy infrastructure.
- **Intervention (I):** Application of IoT sensor networks and/or artificial intelligence (AI) analytics — including machine learning and deep learning — for carbon emissions monitoring, prediction, or accounting.
- **Comparators (C):** Traditional carbon monitoring methods (manual reporting, periodic assessments, conventional statistical models) or systems lacking IoT/AI integration.
- **Outcomes (O):** Accuracy, reliability and scalability of emissions monitoring; predictive performance of AI models; effectiveness of carbon accounting and MRV frameworks; degree of IoT–AI system integration.
- **Study Designs (S):** Peer-reviewed empirical studies, experimental prototypes, framework developments, systematic reviews and literature

reviews published in English from 2021 to 2025.

This review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) reporting guidelines. No systematic review protocol was pre-registered.

1.4 Research Objectives

- To examine IoT-based carbon monitoring systems and their architectural approaches
- To analyse AI and machine learning models used for carbon emission forecasting
- To evaluate carbon accounting and MRV frameworks and their digital implementations
- To identify research gaps in integrated IoT–AI carbon management systems

Section 2 details the methodology applied to identify and analyse relevant literature. Sections 3 to 6 present the synthesised findings across four thematic areas: IoT-based monitoring systems, AI-based forecasting, carbon accounting and MRV frameworks and integrated systems. Section 7 presents research gaps, Section 8 the conceptual framework and Section 9 the Discussion, which includes a summary of main findings, limitations and conclusions.

2 Methods

2.1 Study Design

This study employed a systematic literature review (SLR) methodology to locate, assess and synthesise academic evidence on the use of digital technologies for carbon emissions monitoring and forecasting. Systematic reviews provide transparent and reproducible processes for analysing large volumes of literature and are widely adopted in environmental and information systems research [20]. This review was conducted and reported in accordance with the PRISMA 2020 guidelines [38].

2.2 Search Strategy and Data Sources

A structured search was conducted across five major academic databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect and Google Scholar. Searches were conducted between January and March 2025, covering publications from 2021 to 2025. The following keyword combinations were applied using Boolean operators:

- ("Internet of Things" OR "IoT") AND ("carbon emission" OR "greenhouse gas" OR "CO2 monitoring")
- ("machine learning" OR "deep learning" OR "artificial intelligence") AND ("carbon forecasting" OR "emission prediction")
- ("carbon accounting" OR "MRV" OR "measurement reporting verification") AND ("digital" OR "blockchain" OR "automated")
- ("IoT" AND "AI") AND ("carbon management" OR "carbon accounting" OR "emissions monitoring")

2.3 Inclusion and Exclusion Criteria

Studies were included if they: (1) were published in peer-reviewed journals or conference proceedings; (2) were published in English between 2021 and 2025; (3) focused on IoT-based environmental monitoring, AI-based carbon forecasting, carbon accounting/MRV frameworks, or the integration of these technologies; and (4) provided sufficient methodological detail to assess study quality. Studies were excluded if they: (1) focused solely on non-carbon environmental pollutants without relevance to greenhouse gas monitoring; (2) lacked sufficient methodological description; (3) were grey literature, theses, or editorial commentary; or (4) reported on unpublished or preliminary data.

2.4 Study Selection and Data Extraction

Following initial database searches, duplicate records were removed. Titles and abstracts were screened by the primary reviewer against the inclusion/exclusion criteria. Full texts of potentially eligible studies were then retrieved and assessed. Data were extracted systematically across the following variables: author(s), year, methodology, study context, key findings and implications. The full characteristics of all 100 included studies, organised by thematic category, are presented in Supplemental File Tables S1, S2, S3 and S4. While all 100 included studies are fully characterised in Supplemental Tables S1–S4, the narrative synthesis in Sections 3–6 draws primarily on a representative subset of these studies for detailed discussion, selected to illustrate the range of methodologies, contexts and findings within each thematic area. Readers seeking the complete evidence base for each theme should consult the corresponding supplemental table.

2.5 PRISMA Flow Diagram

The study selection process is summarised in Table 1, consistent with PRISMA 2020 reporting requirements. A total of 843 records were identified through database searches. After removing 187 duplicates, 656 records were screened. Of these, 398 were excluded based on title and abstract review. The remaining 258 full-text articles were assessed for eligibility, with 158 excluded due to insufficient methodological detail, low quality, or being out of scope. A total of 100 studies were included in the final review.

Table 1 presents the PRISMA 2020 flow diagram illustrating the systematic search and study selection process. Records were identified across five databases (Scopus, Web of Science, IEEE Xplore, ScienceDirect and Google Scholar). Following removal of duplicates, title/abstract screening and full-text eligibility assessment, 100 studies were included in the final review.

2.6 Assessment of Risk of Bias

Study quality and risk of bias were assessed using a custom appraisal rubric adapted from the Mixed Methods Appraisal Tool (MMAT). Each study was evaluated on four criteria: (1) clarity and appropriateness of research design; (2) quality and representativeness of data sources; (3) rigour of analysis and result interpretation; and (4) generalisability of findings. Studies were rated as Low, Moderate, or High risk of bias. The results of this assessment are presented in Table 2, summarised by thematic category.

The majority of included studies (54% overall) were rated as low risk of bias, indicating sound methodological quality. Moderate risk (36%) was most common among framework development and prototype studies, where empirical validation was limited to controlled or small-scale settings. Studies rated high risk (10%) were primarily conceptual analyses lacking empirical testing. These findings are considered in the interpretation of synthesised evidence throughout this review.

3 IoT-Based Carbon Emissions Monitoring Systems

3.1 IoT Sensor Networks for Environmental Monitoring

IoT sensor networks have become a foundational technology for environmental monitoring, enabling continuous atmospheric measurement through distributed sensors. Studies consistently demonstrate that IoT systems based on networked sensors can measure carbon dioxide concentration, methane emissions, temperature and humidity with high spatial and temporal resolution. Fay and Corcoran [13] (2024) developed a low-power IoT sensing system capable of detecting carbon emission events in real time using microcontroller-based sensor nodes. Spachos and Hatzinakos [25] (2015) designed a compact wireless CO_2 sensor for indoor air monitoring. These works confirm that distributed sensing architectures substantially outperform traditional manual measurement in temporal resolution, a finding consistent with broader IoT environmental sensing deployments across urban monitoring domains [33] and are increasingly deployed in smart buildings, agricultural systems and industrial facilities. The scalability of IoT sensor deployments makes them particularly well-suited to large and complex monitoring environments where traditional point-sampling methods would be impractical. This scalability also supports the granular spatial mapping of emission hotspots within industrial zones and urban districts, enabling more targeted and effective carbon reduction interventions.

IoT monitoring accuracy is further enhanced when paired with communication and cloud computing infrastructure. Zhu et al. [60] (2022) combined IoT sensing with LSTM forecasting to track indoor CO_2 and demonstrated that real-time measurements enable effective carbon level prediction. Marquez-Zepeda et al. [34] (2025) confirmed that low-cost, internet-connected CO_2 sensors can reliably predict indoor carbon concentrations over both short and long time horizons. Despite these advances, large-scale deployments face calibration drift and sensor reliability concerns, indicating that standardised calibration protocols remain necessary for quality assurance; moreover, the practical value of real-time CO_2 data depends not only on sensor accuracy but also on its effective translation into occupant awareness and behavioural change [15]. This highlights a critical trade-off in IoT-based monitoring: while low-cost sensors lower the barrier to widespread deployment, their long-term accuracy depends on systematic maintenance regimes that are often absent in resource-constrained settings. Addressing this trade-off through self-calibrating sensor designs and remote diagnostics is an active area of engineering research that could substantially improve the reliability of IoT monitoring networks at

Table 1. PRISMA flow of study selection.

PRISMA Stage	Count	Details
Records identified (database search)	843	Scopus ($n = 241$), Web of Science ($n = 198$), IEEE Xplore ($n = 167$), ScienceDirect ($n = 143$), Google Scholar ($n = 94$)
Duplicate records removed	187	Duplicates identified and removed prior to screening
Records screened (title/abstract)	656	Screened against inclusion/exclusion criteria
Records excluded	398	Off-topic ($n = 198$), non-peer-reviewed ($n = 89$), language ($n = 52$), pre-2021 ($n = 59$)
Full-text articles assessed for eligibility	258	Full-text retrieval and quality assessment
Full-text excluded	158	Insufficient methodological detail ($n = 67$), low quality ($n = 54$), out of scope ($n = 37$)
Studies included in the review	100	IoT monitoring ($n = 25$), AI forecasting ($n = 25$), Carbon accounting/MRV ($n = 25$), Integration ($n = 25$)

Table 2. Assessment of risk of bias by thematic category.

Theme	Studies (n)	Low Risk (%)	Moderate Risk (%)	High Risk (%)	Notes
IoT Monitoring	25	52%	36%	12%	Low-cost sensor studies carry calibration uncertainty; prototype deployments lack longitudinal validation.
AI Forecasting	25	60%	32%	8%	Deep learning studies generally well-reported; some lack external validation datasets or geographic transferability.
Carbon Accounting / MRV	25	56%	36%	8%	Empirical governance studies strong; framework proposals carry higher risk due to lack of empirical testing.
IoT-AI Integration	25	48%	40%	12%	Integration studies are often conceptual or pilot-scale; limited large-scale empirical evidence of combined system performance.

scale.

3.2 IoT Architectures for Carbon Monitoring

Carbon monitoring IoT architectures typically operate across three layers: sensing, communication and application/analytics. The sensing layer collects environmental data through distributed sensor nodes [13], an architectural pattern shared with other distributed urban IoT sensing systems [33]. The communication layer — employing Wi-Fi, LoRaWAN, Zigbee, or cellular networks — transmits data to centralised platforms [36, 60]. The analytics layer processes environmental data streams using machine learning models or data analytics software to generate actionable insights [34, 55]. Recent studies also highlight the integration of IoT architectures with blockchain systems, digital twins and Building Information Modelling (BIM) to enhance transparency and carbon accounting traceability [27, 56]. This multi-layer architecture reflects the increasing complexity of carbon monitoring requirements, as organisations move beyond simple data collection towards integrated platforms capable of real-time decision support. The convergence of sensing, connectivity, and analytics within a unified architectural framework is a defining characteristic of next-generation smart environmental monitoring systems, enabling organisations to respond dynamically to emission events rather than relying on retrospective reporting cycles.

3.3 Limitations of Existing IoT Monitoring Systems

Despite widespread adoption, several limitations affect current IoT monitoring systems. Sensor accuracy and calibration remain significant challenges, particularly for low-cost devices deployed in variable

environmental conditions, as demonstrated by deployments in public buildings where continuous CO_2 monitoring served as a practical operational indicator under real-world conditions [11]. Communication infrastructure limitations — including bandwidth constraints, network congestion and connectivity failures — can interrupt continuous environmental data streams [36, 60]. Critically, most IoT monitoring platforms are designed primarily for data collection and lack mechanisms to translate sensor outputs into standardised carbon accounting indicators [27, 34]. This integration gap between environmental monitoring and carbon accounting represents a principal research challenge identified across the reviewed literature. Without standardised interfaces between sensor data outputs and carbon accounting software, the full value of real-time IoT monitoring cannot be realised within formal emissions reporting processes. Bridging this gap requires not only technical interoperability solutions but also the development of agreed data standards and governance frameworks that ensure sensor-derived emissions data meets the rigorous verification requirements of regulatory and market-based carbon systems.

4 Artificial Intelligence for Carbon Emission Prediction

4.1 Machine Learning Approaches for Emission Forecasting

Machine learning models have demonstrated strong performance in predicting carbon emissions by capturing complex relationships among environmental, economic and energy-related variables. Studies confirm that ML algorithms including random forest, support vector machines and extreme learning machines outperform traditional statistical models in emission forecasting accuracy. Zhao et al. [59] (2022) applied a hybrid ML approach combined with factor analysis to forecast carbon emissions in the Yellow River Basin, demonstrating superior predictive performance over regression baselines. Kong et al. [22] (2022) developed an optimised extreme learning machine for daily carbon emission prediction with enhanced accuracy. Ene Yalcın [12] (2024) conducted a comparative study across multiple ML algorithms for sectoral GHG forecasting in Turkey, confirming the superiority of ensemble and nonlinear models. Dataset quality and temporal resolution remain critical determinants of model performance [1, 24]. This dependency on data quality underscores the importance of investing in robust environmental monitoring infrastructure as a prerequisite for deploying effective AI-based emission forecasting systems. Furthermore, the transferability of trained ML models across different geographic regions and industrial contexts remains a challenge, as models optimised for one economic or climatic context may generalise poorly to settings with different emission drivers and data characteristics.

4.2 Deep Learning Models for Environmental Forecasting

Deep learning models offer additional predictive capacity through automatic feature learning from large environmental datasets. Han et al. [16] (2023) demonstrated that a hybrid CNN-LSTM architecture outperformed individual deep learning models for provincial carbon emission forecasting across 30 Chinese provinces. Hu et al. [18] (2024) applied a PSO-LSTM hybrid model to building sector emissions forecasting, achieving superior accuracy over conventional methods. Chen et al. [8] (2025) integrated the STIRPAT framework with a GA-BiLSTM model for provincial carbon peak prediction. A key limitation of deep learning approaches is interpretability: many architectures function as black-box systems, limiting their utility for policy decision-making. Chen et al. [7] (2024) and Sireesha et al. [19] (2025) addressed this through explainable AI frameworks, demonstrating that interpretability and predictive accuracy can be balanced in environmental forecasting contexts. The growing adoption of explainable AI techniques in environmental science reflects broader recognition that regulatory acceptance of AI-driven decision tools depends as much on the ability to explain predictions as on their technical accuracy. As deep learning models are increasingly considered for use in official emissions reporting and compliance monitoring, their explainability will become a non-negotiable requirement rather than an optional enhancement.

4.3 AI in Smart Energy and Carbon Reduction Systems

AI is increasingly applied to enhance energy efficiency and reduce operational carbon emissions across sectors. Yang et al. [57] (2024) demonstrated that random forest-based scenario modelling can accurately project city-level carbon emission trends and peak timing, providing a foundation for AI-informed regional decarbonisation planning that complements building-level energy management optimisation. Arun et al. [3] (2024) confirmed

that deep learning models can identify inefficient energy consumption patterns and generate actionable optimisation recommendations for existing buildings. Franco et al. [14] (2022) and Wang et al. [50] (2025) showed that AI forecasting models support long-term low-carbon energy planning in cities and buildings, respectively. Successful implementation, however, requires high-quality data and interoperable digital infrastructure [10, 59]. The integration of AI into energy management also introduces questions of cybersecurity and system resilience, as AI-controlled energy infrastructure becomes a potential target for disruption. Beyond technical requirements, the successful deployment of AI-driven carbon reduction systems depends on organisational capacity to interpret and act on AI-generated recommendations, pointing to the need for digital literacy and institutional change management alongside technical implementation.

4.4 Challenges in AI-Based Emission Prediction

Despite demonstrated predictive capabilities, AI-based emission forecasting faces significant challenges. Data availability and quality are primary obstacles, as inconsistent or low-resolution historical datasets degrade model performance [1, 24]. Model interpretability remains a concern, particularly for deep learning architectures deployed in policy-relevant contexts [7]. Geographic transferability is a further limitation: models trained on data from one region may require substantial recalibration when applied to contexts with different economic structures or energy systems [12, 59]. These challenges underscore the need for robust data infrastructure, standardised training datasets and explainable modelling frameworks in operationally deployed AI emission systems. Overcoming these challenges will require coordinated efforts across research institutions, technology developers and regulatory bodies to establish minimum data quality standards, model validation protocols and transparency requirements for AI tools used in environmental governance. Without such frameworks, the risk of over-reliance on poorly validated AI models in high-stakes climate policy decisions remains a significant concern for the scientific community.

5 Carbon Accounting and MRV Frameworks

5.1 Principles of Carbon Accounting

Carbon accounting is the systematic process of recognising, quantifying, categorising and reporting greenhouse gas emissions associated with organisational operations, products, or projects. He et al. [17] (2022) traced its evolution from a compliance-based reporting tool to a broader governance instrument for climate performance monitoring and mitigation strategy. Tang et al. [37] (2014) and Cordova et al. [9] (2021) demonstrated that institutional quality and internal governance structures are key determinants of carbon accounting effectiveness. Core principles include standardised emission boundary definitions, transparent conversion of activity data to CO_2-equivalent values and independent verification of reported emissions [4, 29]. These principles are not merely technical requirements but reflect a broader political and institutional commitment to transparency in climate governance, where the credibility of national and organisational emissions claims depends on the robustness of the accounting methods underpinning them. As carbon markets and regulatory frameworks expand globally, the harmonisation of carbon accounting standards across jurisdictions has become an increasingly urgent priority to ensure that emissions data from different sources can be meaningfully compared and aggregated.

5.2 Measurement, Reporting and Verification (MRV)

MRV frameworks provide the institutional infrastructure for credible carbon accounting and climate governance. He et al. [17] (2022) established that MRV systems emerged in response to the need for transparent emissions reporting under climate governance frameworks. Brown and MacAskill [5] (2025) confirmed that sound MRV systems are foundational to effective urban carbon management. Thornbush and Govind [48] (2025) identified MRV frameworks as essential to carbon trading accountability. The measurement component requires standardised protocols for activity data collection [4, 39]. Verification increasingly relies on digital platforms, including blockchain-based systems, to produce immutable audit records [23, 52]. The digitalisation of MRV processes represents a significant opportunity to reduce the cost and time associated with traditional manual verification, while simultaneously increasing the frequency and coverage of emissions audits. However, the transition to digital MRV systems requires substantial investment in data infrastructure, technical capacity and regulatory adaptation, which poses particular challenges for developing nations seeking to implement credible

climate governance frameworks under resource constraints.

5.3 Carbon Credit Accounting Systems

Carbon credit accounting systems quantify and document verified emission reductions tradeable in carbon markets. Perosa et al. [39] (2023) demonstrated that credible carbon credits require robust monitoring and reporting mechanisms. Batjes et al. [4] (2024) highlighted the importance of uniform accounting processes for calculating carbon sequestration in land-use systems. Knapp et al. [21] (2023) and Reershemius et al. [42] (2023) validated empirical measurement protocols for carbon dioxide removal. Digital technologies, particularly blockchain and integrated data management systems, are increasingly used to enhance transparency and prevent double-counting in carbon credit systems [23, 32, 56]. The integrity of carbon credit markets ultimately depends on the quality of the underlying accounting systems, and any weaknesses in measurement or verification can undermine confidence in carbon offsetting as a climate mitigation tool. As voluntary carbon markets continue to grow, the development of universally accepted digital accounting standards for carbon credits has become a strategic priority for international climate finance institutions and regulatory bodies seeking to scale market-based emissions reduction mechanisms.

5.4 Limitations of Existing Carbon Accounting Platforms

Current carbon accounting platforms face methodological inconsistencies, data reliability gaps and technological integration deficits. He et al. [17] (2022) and Li et al. [30] (2024) identified variability in accounting boundaries and emission factor assumptions as sources of comparability problems across organisations and sectors. Perosa et al. [39] (2023) and Batjes et al. [4] (2024) noted that incomplete monitoring data undermines the credibility of accounting systems, particularly in agricultural and ecosystem contexts. Traditional accounting systems generally lack automated data verification mechanisms, increasing misreporting risk [52]. Körner et al. [23] (2025) found that most existing platforms have yet to achieve full integration with real-time monitoring technologies such as IoT sensor networks, representing a key gap for future system development. The persistence of these limitations reflects structural inertia within existing reporting systems, where organisations and regulators have invested heavily in established accounting methodologies that are difficult to reform even when superior digital alternatives are available. Overcoming this inertia will require regulatory incentives, capacity building and the development of transition pathways that allow organisations to migrate from legacy carbon accounting platforms to integrated digital systems without disrupting their existing compliance obligations.

6 Integration of IoT, AI and Carbon Accounting Systems

6.1 Smart Carbon Monitoring Platforms

Smart carbon monitoring platforms combine IoT sensor networks with data analytics and carbon accounting capabilities within integrated digital infrastructures. Wu et al. [53] (2025) identified that leading smart carbon platforms in the architecture, engineering and construction sector commonly incorporate sensors, BIM systems and data platforms to monitor carbon emissions dynamically. Liu et al. [27] (2020) developed a BIM-IoT integrated platform for real-time construction carbon tracking. Das [10] (2025) confirmed that AI-enabled digital monitoring platforms substantially improve energy efficiency and carbon management in smart buildings. Pourrahmani et al. [41] (2025) demonstrated that integrating sensor networks with AI analytics enhances both monitoring accuracy and forecasting performance. These integrated platforms represent a fundamental shift in how organisations conceptualise carbon management, moving from periodic compliance reporting towards continuous situational awareness of their emissions profile. The ability to monitor, analyse and respond to carbon emissions in near real-time enables proactive management strategies that were previously impossible with conventional reporting systems, offering significant potential to accelerate the pace of organisational decarbonisation.

6.2 Digital Carbon Management Systems

Digital carbon management systems represent fully integrated technological platforms for measuring, analysing, reporting and controlling greenhouse gas emissions. He et al. [17] (2022) described a shift from static inventory-based carbon management to dynamic digital systems. Liu et al. [27] (2020) showed that BIM-IoT systems can connect field-level data collection to carbon accounting functions in construction. Woo et al. [52] (2020) demonstrated that blockchain-based

platforms enhance the traceability and auditability of carbon data, while Luo et al. [31] (2021) showed that robust internal governance structures and strategic climate-risk awareness are equally critical preconditions for translating monitoring outputs into credible carbon performance outcomes. Körner et al. [23] (2025) established that digital MRV infrastructures integrating monitoring, reporting and verification within a single digital process are central to scalable carbon management. The emergence of digital carbon management systems also creates new opportunities for supply chain transparency, enabling organisations to track embedded carbon across complex multi-tier supplier networks in ways that were previously impractical. As sustainability reporting requirements tighten globally under frameworks such as the EU Corporate Sustainability Reporting Directive and the IFRS Sustainability Standards, demand for robust digital carbon management infrastructure is expected to grow substantially across both public and private sector organisations.

6.3 Challenges in Integrated Systems

Integrated carbon monitoring systems face significant technological, data and governance challenges. Pourrahmani et al. [41] (2025) and Wu et al. [53] (2025) identified interoperability between heterogeneous sensing, analytics and accounting platforms as a primary technical barrier, requiring standardised data formats and communication protocols. Liu et al. [27] (2020) noted that differences in data structures and system architectures complicate the merging of operational monitoring with carbon accounting frameworks. Brown and MacAskill [5] (2025) and Thornbush and Govind [48] (2025) highlighted that weak data infrastructure in some regions limits the scalability of integrated digital carbon systems. Governance and institutional challenges — including cross-organisational data sharing, regulatory alignment and stakeholder coordination — further constrain implementation [23, 35, 56]. Resolving these governance challenges is as important as addressing technical interoperability barriers, since even technically superior integrated systems will fail to achieve widespread adoption if they cannot be embedded within existing organisational reporting structures and regulatory compliance workflows. The development of shared governance models for multi-stakeholder carbon data platforms — including clear rules on data ownership, access rights and liability — is therefore a critical enabling condition for the transition to integrated digital carbon management at scale.

7 Research Gaps

The analysis of reviewed literature identifies four principal research gaps. First, despite widespread deployment of IoT sensor networks, most research focuses on data collection without integrating sensor outputs into standardised carbon accounting systems, a pattern observed broadly across urban IoT monitoring applications [33] and specifically within carbon monitoring platforms [53]. Second, while ML and deep learning models demonstrate strong emission forecasting performance, the majority of these models operate independently from real-time monitoring systems and are not coupled with live IoT data streams [24, 59]. Third, existing carbon accounting platforms predominantly rely on periodic, manually aggregated reporting rather than automated continuous emissions tracking [5, 17]. Fourth, despite emerging research on digital MRV systems and blockchain-based carbon management, the literature lacks sufficient empirical evidence of fully integrated systems. No single operational platform has yet been demonstrated that combines IoT monitoring, AI-based forecasting and carbon accounting end-to-end [23, 41]. A fifth gap concerns geographic coverage. The overwhelming majority of reviewed studies were conducted in high-income countries or China. This leaves a significant evidence gap regarding IoT–AI carbon monitoring systems in sub-Saharan African, South Asian and Latin American contexts. These are precisely the regions where monitoring infrastructure is least developed, yet emissions growth trajectories are most consequential for global climate outcomes.

8 Conceptual Framework for IoT–AI Carbon Accounting

Based on the synthesised evidence, a conceptual framework is proposed to describe the relationships between the key variables under review.

Independent Variables: (1) IoT-Based Environmental Monitoring — the deployment of interconnected sensor networks collecting real-time environmental data including CO_2 concentration, methane levels, temperature and energy consumption. (2) Artificial Intelligence Analytics — the application of machine learning and deep learning algorithms to analyse environmental datasets, detect emission patterns and forecast carbon emission trends.

Dependent Variable: Carbon Accounting Output —

the quantified amount of greenhouse gas emissions expressed as CO_2 equivalent (CO_2e), formatted for regulatory reporting, carbon market participation, or environmental standards compliance.

Mediating Variable: MRV System — the systematic protocol for transforming monitored environmental data into standardised carbon accounting reports through validated measurement and reporting procedures.

IoT environmental monitoring provides real-time input data to AI analytics, which applies these sensor streams to generate predictive emission forecasts and detect anomalous patterns. MRV frameworks then translate these outputs into standardised carbon accounting results expressed as CO_2-equivalent values. This sequence illustrates how integrated digital technologies can convert raw sensor data into verified carbon accounting outputs suitable for climate governance. The framework further implies that weaknesses at any stage of this chain — whether in sensor reliability, AI model accuracy or MRV protocol design — will propagate through to the quality of the final carbon accounting output. This systemic interdependency reinforces the argument that IoT, AI and MRV components must be co-designed and validated as an integrated system rather than developed in isolation, if the full potential of digital carbon management is to be realised in practice.

9 Discussion

9.1 Summary of Main Findings

This systematic review synthesised evidence from 100 peer-reviewed studies across four thematic areas. The findings confirm that IoT sensor networks provide a scalable foundation for continuous real-time environmental monitoring, substantially improving the spatial and temporal resolution of emissions data compared to traditional manual methods. AI-based forecasting models, particularly hybrid deep learning architectures, demonstrate strong predictive performance for carbon emissions across diverse sectors and geographic contexts. Carbon accounting and MRV frameworks provide the necessary institutional infrastructure to translate monitoring data into standardised, verifiable emissions reports. However, a critical integration gap persists. The majority of reviewed systems operate within siloed technological domains. No large-scale, empirically validated platform has yet been demonstrated that fully integrates real-time IoT monitoring, AI-based forecasting and automated carbon accounting within a single operational system.

The conceptual framework developed in this review proposes that MRV systems serve as the critical mediating layer between digital monitoring inputs and verified carbon accounting outputs. This framing has direct implications for system designers and policymakers seeking to build credible, scalable digital carbon management infrastructure. In particular, investment in MRV capacity building should be treated as equally important as investment in sensing and analytics hardware. Even the most sophisticated IoT and AI systems will fail to generate regulatory-grade emissions data without the institutional and procedural infrastructure to verify and validate their outputs. These findings collectively point towards the need for a whole-of-system approach to digital carbon management that integrates technological, institutional and governance dimensions within a coherent design framework.

9.2 Limitations

This review has several limitations. First, the search was restricted to five databases and English-language publications, which may have excluded relevant studies published in other languages or indexed in specialised repositories. Second, studies were not formally weighted by evidence quality in the thematic synthesis, though risk of bias assessments were conducted to contextualise findings. Third, the review period of 2021–2025, while appropriate for capturing recent technological developments, excludes foundational earlier literature on carbon accounting and IoT systems that may provide additional historical context. Fourth, the absence of a pre-registered review protocol, while common for this type of review, limits reproducibility. Future systematic reviews in this field would benefit from protocol pre-registration via PROSPERO or an equivalent registry.

9.3 Implications for Future Research

Future research should prioritise the development of empirically validated integrated platforms that combine IoT sensor infrastructure, AI-based analytics and carbon accounting frameworks into cohesive digital systems. Further work is needed to enhance the interoperability of heterogeneous monitoring and accounting platforms through standardised data models and communication protocols. Research on explainable AI approaches for emission forecasting would improve the policy

relevance and regulatory acceptance of AI-driven monitoring tools. Additionally, investigations into digital MRV implementation in data-sparse or resource-constrained contexts — particularly in the Global South — would address a significant equity gap in the current literature. Zimbabwe's recent regulatory developments offer a concrete case study for this agenda: the Carbon Trading (General) Regulations, 2025 (Statutory Instrument 48 of 2025, gazetted 2 May 2025 under Section 73 of the Environmental Management Act [Chapter 20:27]) established the Zimbabwe Carbon Markets Authority (ZiCMA) and mandated a national blockchain-based carbon registry, yet the ground-level digital MRV infrastructure required to feed verified sensor data into this registry remains underdeveloped. Future research should examine how integrated IoT–AI–MRV systems can be deployed to operationalise such nationally mandated digital carbon governance frameworks, particularly in emerging economy contexts where regulatory ambition currently outpaces technical capacity. Collaboration between research institutions, technology providers and policymakers across different national contexts will be essential to ensure that the benefits of digital carbon management technologies are accessible beyond high-income settings where most current research has been conducted. International development frameworks and climate finance mechanisms could play a catalytic role here. These mechanisms could support the deployment and evaluation of integrated IoT–AI carbon monitoring systems in regions where the need for reliable emissions data is greatest but existing monitoring infrastructure is most limited.

10 Conclusions

This review examined 100 peer-reviewed studies on IoT-based carbon sensing, AI-based emissions forecasting, carbon accounting frameworks and the integration of digital technologies in environmental management. IoT sensor networks enable continuous environmental data collection, while machine learning and deep learning models support reliable emissions prediction and climate-informed decision-making. Carbon accounting and MRV systems provide the institutional mechanisms to convert monitoring data into standardised emissions reports. Nonetheless, persistent challenges in data quality, system interoperability and the disconnection between monitoring technologies and carbon accounting platforms limit the full potential of digital carbon management. Addressing these challenges is essential to building efficient, credible and scalable digital carbon management systems capable of supporting climate governance, sustainability reporting and the practical implementation of carbon reduction strategies. The findings of this review ultimately underscore that the technological components necessary for effective digital carbon management already exist and have been demonstrated at prototype or pilot scale. The central challenge now is not invention but integration. The task is to design systems that bring IoT sensing, AI analytics and MRV frameworks together into coherent, interoperable platforms. These platforms must be institutionally embedded and capable of operating reliably at the scale required by national and international climate governance commitments.

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Appendix: Supplemental File

Table S1. IoT-Based Carbon Emissions Monitoring Systems.

Author(s)	Year	Methodology	Context	Key Findings	Implication	DOI
Fay, Corcoran, & Diamond	2024	Prototype design and event-detection testing on low-power microcontrollers	Sensor networks for carbon-emission event monitoring	Demonstrated resource-efficient real-time event detection for carbon-emission monitoring	Supports low-power IoT architectures for continuous emissions surveillance	10.3390/s24010162
Li, Pandey, & Pandey	2025	IoT tool development and implementation study	Anaerobic reactors / biogas systems	IoT improved real-time monitoring of GHG emissions in reactor environments	Useful for agricultural waste and bioenergy emissions monitoring	10.3390/en18236191
Bilotta et al.	2022	Traffic-sensor data modelling and reconstruction	Road traffic / transport emissions	IoT traffic-flow sensors can estimate CO_2 emissions under congested and uncongested conditions	Enables near-real-time transport carbon tracking for smart mobility systems	10.3390/s22093382
Kuncoro, Amaris, & Permana	2022	Hardware prototype and system evaluation	Indoor CO_2 monitoring	Developed a compact wireless CO_2 sensor node for strategic indoor monitoring	Supports affordable IoT CO_2 monitoring in enclosed environments	10.3390/app12110784
Zhu, Al-Ahmed, Shakir, & Olszewska	2023	IoT system development plus LSTM forecasting	Indoor air-quality monitoring	Combined low-cost IoT sensing with CO_2 steady-state forecasting	Strengthens predictive indoor carbon monitoring and ventilation support	10.3390/electronics12010107
Marquez-Zepeda et al.	2025	Low-cost system design plus LSTM evaluation	Indoor shared spaces	Scalable NDIR-based IoT platform predicted short- and long-term CO_2 concentrations	Valuable for proactive ventilation and smart-building carbon management	10.3390/mca30020036
Dadallage et al.	2025	Technical note; system development and field deployment	Precision dairy farming	Built a real-time IoT greenhouse-gas and weather monitoring system for dairy operations	Extends livestock emissions monitoring with integrated farm sensing	10.3168/jdsc.2025-0862
Gabriel et al.	2024	Large-scale deployment and user-intervention study	84 homes with children	Real-time IoT feedback helped reduce indoor CO_2 levels and improve IAQ awareness	Shows household IoT monitoring can drive healthier behavioral change	10.1016/j.buildenv.2024.112040
Di Gilio et al.	2021	Pilot real-time surveillance study	Educational buildings / classrooms	Continuous CO_2 monitoring was effective as a strategic indicator for indoor risk control	Demonstrates operational value of CO_2 sensing in public buildings	10.1016/j.envres.2021.111560
Jaya et al.	2025	IoT monitoring system design and implementation	Paddy fields / agriculture	Developed an IoT system for methane-related GHG monitoring and soil-health tracking	Useful for climate-smart agriculture and emissions-aware farming	10.18502/kls.v9i1.19350
Li et al.	2025	BIM-IoT platform development and evaluation	Prefabricated building materialization	Platform improved real-time carbon tracking accuracy and source traceability	Important for construction-stage carbon accounting and control	10.1016/j.resconrec.2025.108122
D'Urso et al.	2025	In-field performance evaluation	Livestock buildings	IoT monitoring system effectively tracked particulate pollution in real conditions	Relevant for broader smart livestock emission and air-quality surveillance	10.3390/s25164987
Caraveo Mena et al.	2025	Distributed IoT system design and implementation	Vehicles using biofuels	Low-cost ESP32-based network monitored combustion gases across vehicles	Supports fleet-level emissions comparisons and cleaner transport monitoring	10.3390/su17031153
Rus et al.	2025	Comparative sensor evaluation	Educational facilities	KNX and IoT sensor data showed strong agreement for CO_2 monitoring when maintained properly	Validates smart-building monitoring infrastructure for school environments	10.3389/fbuil.2025.1688582
Kim et al.	2023	IoT sensing plus machine-learning estimation	Occupancy-aware ventilation management	CO_2 and pressure data enabled occupancy estimation from indoor sensing	Useful for demand-controlled ventilation and indirect carbon-control strategies	10.3390/s23020585
Zhao et al.	2025	One-year field monitoring and data-driven analysis	Office buildings	Long-term CO_2 and PM monitoring identified better sensor placement and sampling strategies	Improves efficiency and accuracy of office IoT monitoring deployments	10.1016/j.buildenv.2025.113392
Hassan et al.	2025	Experimental filtration plus IoT-based monitoring	Gasoline-engine emissions	Combined CO_2 removal with IoT-based emissions monitoring in engine exhaust applications	Suggests integrated mitigation-plus-monitoring approaches for mobile emissions	10.3390/polym17111447
Wu & Gao	2021	Multimodal regression using energy and air-quality data	Factories / industrial emissions	Model monitored factory emissions using multimodal data where direct measurement was unreliable	Useful for industrial proxy-based emissions surveillance	10.3390/su13052663
Arun et al.	2024	IoT sensing integrated with deep-learning energy modelling	Older buildings	IoT-enabled deep-learning monitoring improved energy-efficiency decision-making	Indirectly supports lower operational carbon emissions in aging buildings	10.1016/j.csite.2024.104867
Mota et al.	2025	IoT architecture implementation and case study	Indoor air quality during sleep periods	ESP32-C6, MQTT, and InfluxDB architecture enabled real-time CO_2 and PM monitoring	Provides a replicable low-cost architecture for continuous indoor monitoring	10.3390/s25061683
Sabando-Bravo, Navia, & Zambrano-Martinez	2025	Simulation plus physical implementation	Urban CO_2 monitoring network design	Evaluated alternative sensor-network layouts for city-level CO_2 monitoring	Helps optimize placement of urban carbon-monitoring nodes	10.3390/jsan14050093
Xiao, Ghafoorpoor Yazdi, & Thiede	2025	Prototype development and pilot-factory validation	Smart factory	Dynamic CO_2 map captured spatiotemporal distribution with low relative error	Strong for factory carbon visibility, safety, and HVAC optimization	10.1016/j.procir.2025.02.191
Christensen	2025	Literature review and use-case analysis	Industrial and environmental domains	Synthesized IIoT technologies for real-time CO_2 monitoring, measurement, and visualization	Useful framing study for industrial carbon-monitoring architectures	10.1007/978-3-031-78572-6_3
Xu et al.	2022	Conceptual framework and system proposal	Prefabricated buildings	Proposed a three-layer IoT-integrated embodied carbon assessment and monitoring system	Important early model for integrating sensing, communication, and carbon analysis	10.1088/1755-1315/1101/2/022031
Zhang et al.	2021	Platform architecture design	Small cities / urban carbon monitoring	Proposed an IoT-cloud smart carbon platform tailored for urban carbon monitoring	Foundational for city-scale digital carbon monitoring systems	10.1007/s11276-021-02756-2

Table S2. Artificial Intelligence for Carbon Emission Prediction.

Author(s)	Year	Methodology	Context	Key Findings	Implication	DOI
Zhao, Kou, Wang, He, Xiong, Liu, & Cui	2022	Hybrid machine-learning prediction with QAP factor analysis	Yellow River Basin, China	ML outperformed simpler baseline approaches in forecasting regional carbon emissions and identifying major drivers	Useful for basin-level carbon governance and targeted regional mitigation	10.3390/su14106153
Kong, Song, & Yang	2022	Two-stage feature selection with optimized extreme learning machine	Daily carbon-emission forecasting	The optimized ELM model improved short-term daily carbon-emission prediction accuracy	Strong option for high-frequency carbon monitoring and operational forecasting	10.1007/s11356-022-21277-9
Franco, Melica, Treville, Baldi, Pisoni, Bertoldi, & Thiel	2022	Machine-learning forecasting framework	Cities and municipalities tracking climate targets	Proposed a city-level GHG forecasting approach using municipal indicators and showed usable predictive performance	Helps local governments monitor progress toward mitigation and adaptation commitments	10.1016/j.scs.2022.104114
Kumari & Singh	2023	Comparative time-series machine-learning models	India national CO_2 emissions	ML-based time-series models produced effective long-range CO_2 forecasts for India	Supports national carbon planning and scenario-based policy design	10.1007/s11356-022-21723-8
Yan, Zhang, Sun, & Wang	2023	Convolutional neural network	Early design-stage residential units in Beijing	CNN enabled real-time prediction of operational carbon emissions at residential-unit design stage	Useful for embedding low-carbon decisions earlier in building design workflows	10.1016/j.jobe.2023.106994
Han, Cui, Xu, Wang, & Guo	2023	Coupled LSTM-CNN deep learning model	30 Chinese provinces	The hybrid CNN-LSTM improved provincial carbon-emission forecasting accuracy over single models	Supports subnational planning where temporal and spatial patterns interact	10.3390/su151813934
Xie, Huang, Tan, & Chen	2024	Comparative deep-learning study	China's agricultural carbon emissions	Deep-learning models delivered strong performance for agricultural carbon-emission forecasting, with model differences by horizon and structure	Demonstrates AI value in agricultural decarbonization analysis	10.1016/j.ecoinf.2024.102661
Hu, Wang, Yang, & Yang	2024	Hybrid improved PSO-LSTM model	Building industry CO_2 emissions	The hybrid optimization–LSTM approach increased forecasting accuracy relative to conventional models	Useful for construction-sector carbon management and planning	10.3390/en17174379
Tu, Wang, Li, Wang, Hu, Luo, Shi, Li, Luo, & Yao	2024	RF-RFE-Deep Forest-Optuna framework	Coal-fired power plants	The optimized ensemble framework achieved accurate CO_2 prediction with improved feature selection and tuning	Valuable for plant-level emissions oversight and operational optimization	10.3390/en17246449
Ene Yalçın	2024	Comparative ML framework using MLR, RF, KNN, XGBoost, SVR, and MLP	Turkey sectoral GHG emissions	Advanced ML algorithms enabled sector-based GHG forecasting using multiple explanatory variables	Useful for economy-wide and sector-specific emissions planning	10.3390/systems12120528
Chen, Guo, Zhang, Wu, & Yang	2024	Explainable deep learning with multi-scale time-series modeling	Building carbon emissions	The model improved robustness and interpretability in building carbon-emission forecasts	Supports deployable building AI systems where explainability matters	10.1016/j.enbuild.2024.114159
Zheng, Luo, & Zhao	2024	Comparative machine-learning model development	Urban residential buildings in Guangzhou	ML methods provided a practical operational carbon-emission prediction model for residential buildings	Helps city-scale residential carbon management and smart-building control	10.3390/buildings14113699
Udoh, Ajuonu, Ajaegbu, et al.	2024	Supervised machine-learning modeling	Light-duty vehicle CO_2 emissions	ML models successfully predicted vehicle CO_2 emissions from vehicle-specification datasets	Useful for transport policy, vehicle benchmarking, and fleet emissions screening	10.3390/s24248219
Yang, Chen, Ke, He, Li, Liu, & Li	2024	Random forest with scenario analysis	Regional cities in Jiangsu Province, China	RF-based forecasts estimated city-level carbon-emission trends and peak timing under scenarios	Helpful for regional carbon-peak planning and differentiated city strategies	10.3390/su16231450
Jamei, Yaqoob, Farooque, Ali, Malik, Esau, & Hu	2025	Explainable predictive AI approach	Potato agriculture in Maritime Canada	AI models explained the main drivers of agricultural GHG emissions while forecasting emissions	Useful for climate-smart agriculture and interpretable farm-level mitigation decisions	10.1016/j.atech.2024.100709
Hamedani & Talebi	2025	Optimized artificial neural network with renewable-energy scenarios	Asia-wide CO_2 emissions	ANN-based long-term forecasting captured regional emissions trajectories and scenario effects	Valuable for continental-scale transition planning and scenario analysis	10.1016/j.ecmx.2025.101030
Begum & Mobin	2025	Machine-learning forecasting on multi-country dataset	Top eleven global emitters	The model projected future emissions trajectories and compared them with Paris-aligned prospects	Supports cross-country benchmarking and strategic climate-policy assessment	10.1038/s41598-025-04236-5
Ajala, Adeoye, Salami, et al.	2025	Comparative ML, deep-learning, and statistical modeling	Daily CO_2 emissions in China, India, USA, and EU27+UK	Comparing 14 models showed that AI models can improve daily emissions prediction relative to traditional approaches	Strong evidence for near-real-time policy dashboards and short-term emissions control	10.1007/s11356-024-35764-8
Adam, Yusuf, Amir, et al.	2025	Machine-learning prediction using demographic, economic, energy, and transport variables	Transportation-related GHG emissions in Africa's top emitters	ML effectively forecast transport-sector GHG emissions using multi-factor national data	Useful for African transport decarbonization planning	10.1186/s12302-025-01223-5
Hong, Fu, & Dai	2025	Machine-learning prediction plus regional heterogeneity analysis	30 Chinese provinces	The study combined carbon-emission prediction with province-specific reduction strategy design	Useful for customized provincial policy interventions rather than one-size-fits-all targets	10.3390/su17051786
Tian, Zhang, He, Yuan, Xie, Zhang, & Jing	2025	Machine-learning forecasting	Energy-based CO_2 emissions in the United States	ML provided actionable forecasts linking energy patterns to future U.S. CO_2 emissions	Supports national energy-transition planning and mitigation strategy design	10.3390/su17072843
Almsallti, Alzubi, & Adegboye	2025	Metaheuristic-optimized extreme learning machine	CO_2 prediction using globalization-related indicators	The hybrid ELM approach improved prediction performance using macro-level globalization drivers	Demonstrates the relevance of broader socioeconomic indicators in carbon forecasting	10.3390/su17156783
Chen, Chen, & Guo	2025	Extended STIRPAT with GA-BiLSTM	China provincial carbon peak prediction	Integrating STIRPAT with GA-BiLSTM improved provincial peak prediction and scenario sensitivity	Useful for estimating carbon-peak timing and designing province-level transition pathways	10.3390/su17156819
Zhang, Ma, Wang, Yang, & Wang	2025	Interpretable machine-learning framework with optimization	University campus CO_2 emissions	Interpretable ML predicted campus CO_2 emissions and identified optimization levers	Valuable for campus sustainability management and explainable decision support	10.3390/su17231432
Wang, Tan, Yu, Yu, Wang, & Zhou	2025	Deep hybrid framework integrating enhanced extreme learning machines	Building operational carbon emissions	The hybrid model delivered accurate operational carbon-emission forecasts for buildings	Useful for smart-building carbon control and operational decarbonization	10.1016/j.egyr.2025.03.014

Table S3. Carbon Accounting and MRV Frameworks.

Author(s)	Year	Methodology	Context	Key Findings	Implication	DOI
Woo, Fatima, Kibert, Newman, Tian, & Srinivasan	2021	Systematic literature review	Building energy performance MRV and carbon credit markets	Showed blockchain can strengthen transparency, traceability, and trust in building energy MRV	Useful foundation for digital MRV in buildings and carbon-credit participation	10.1016/j.buildenv.2021.108199
Ong, Kasbun, Teh, Muhamad, & Javeed	2021	Survey-based empirical analysis	Malaysian companies	Found carbon accounting systems act as a bridge between carbon governance and carbon performance	Supports adoption of internal carbon accounting systems for better governance outcomes	10.1080/20964129.2021.1927851
Cordova, Zorio-Grima, & Merello	2021	Empirical governance analysis	Emerging economies	Corporate and contextual governance factors significantly affect carbon accounting and carbon performance	Highlights governance quality as a condition for effective carbon accounting	10.1108/CG-10-2020-0473
Luo & Tang	2021	Empirical corporate analysis	Firms' carbon strategy and climate-risk awareness	Carbon strategy and climate-risk awareness strengthen the governance–carbon performance link	Suggests MRV and accounting systems work best when embedded in strategy	10.1111/acfi.12687
He, Luo, Shamsuddin, & Tang	2022	Literature review	Corporate carbon accounting research	Mapped the evolution of carbon accounting research from Kyoto to Paris and identified persistent methodological gaps	Strong review base for framing carbon accounting literature and gaps	10.1111/acfi.12789
Ong, Kasbun, Abdul Rahman, Meero, & Teh	2022	Mediation analysis	Malaysian firms	Carbon accounting significantly mediates the relationship between carbon risk management and carbon performance	Shows accounting systems are not just reporting tools but performance enablers	10.32479/ijeep.12780
Perosa, Newton, Gil, Piza, Sparovek, Rajão, Telles, & De Oliveira Silva	2023	Case study with interviews and document analysis	Low-carbon agriculture in Brazil	Developed a large-scale MRV perspective for low-carbon agriculture and identified operational bottlenecks across monitoring, reporting, and verification	Important for agricultural MRV system design in developing-country settings	10.1016/j.envsci.2022.12.006
Knapp, Stevenson, Renforth, Ascough, Knight, Bridgestock, Bickle, Lin, Riley, Mayes, & Tipper	2023	Multiproxy measurement framework	Enhanced rock weathering sites	Proposed a robust multiproxy method for quantifying CO_2 removal at field sites	Advances empirical MRV for carbon dioxide removal projects	10.1021/acs.est.3c03757
Reershemius, Kelland, Kantola, DeLucia, Silver, Paustian, & Beerling	2023	Proof-of-concept experimental method	Enhanced rock weathering in soils	Validated a soil-based mass-balance approach for empirical MRV of weathering rates	Offers a potentially scalable measurement protocol for ERW carbon credits	10.1021/acs.est.3c03609
Batjes, Ceschia, Heuvelink, Demenois, le Maire, Cardinael, Arias-Navarro, & van Egmond	2024	Framework development / review	Soil organic carbon stock-change assessment	Proposed a modular, multi-ecosystem MRV framework for SOC accounting	Useful for harmonizing soil-carbon MRV across ecosystems and project types	10.1080/17583004.2024.2410812
Li, Yang, Du, Liu, Zhang, Yang, Zhang, & Liu	2024	Review study	Electricity power industry	Reviewed direct and indirect electricity carbon accounting approaches and their shortcomings	Important reference for power-sector accounting method selection	10.1016/j.apenergy.2024.122681
Li, Fei, Du, Ong, & Arisian	2024	Framework development with applied modeling	Maritime transport	Proposed a near-real-time carbon accounting framework for tracking ship emissions at 15-minute intervals	Supports operational decarbonization and compliance in shipping	10.1016/j.tre.2024.103724
Luo, Shen, Liang, Sun, & Dong	2024	Blockchain tool development with case application	Solar PV systems in Hong Kong's building sector	Developed a blockchain-based MRV tool for life-cycle PV carbon auditing	Strengthens traceability and verification of PV-related carbon accounting	10.1016/j.jclepro.2024.143456
Luo, Shen, Liang, Sun, & Dong	2024	Information-system design and case application	Building life-cycle carbon in Hong Kong	Built a traceable and immutable blockchain-enabled MRV system for embodied carbon	Useful for life-cycle carbon auditing in the built environment	10.1016/j.resconrec.2024.107736
Xu, Tao, Das, Kwok, Liu, Kuan, Lau, & Cheng	2024	Blockchain framework design and evaluation	Construction material and product certification	Proposed GPChain to support transparent carbon data sharing and certification	Relevant for supply-chain carbon certification and product-level traceability	10.1016/j.aei.2023.102242
Alotaibi, Khallaf, Abdallah, Zoubi, & Alnesafi	2024	Design science framework	Supply-chain ESG and carbon reporting	Developed a blockchain-driven framework integrating automated collection, verification, and analysis of emissions data	Useful for accountable supply-chain carbon reporting	10.3390/su16241087
Clarkson, Larkin, Swoboda, Reershemius, Suhrhoff, Maesano, & Campbell	2024	Review article	Enhanced weathering MRV in soils	Reviewed current measurement options for quantifying CDR via enhanced weathering	Helps researchers choose and combine MRV methods in EW projects	10.3389/fclim.2024.1345224
Wolf, Chang, Kantola, Blanc-Betes, Masters, Marklein, Moore, Bernacchi, & DeLucia	2024	Critical methodological validation	Enhanced rock weathering carbon removal	Tested assumptions used in ERW carbon-removal estimation and exposed key uncertainties	Improves rigor in CDR accounting claims and protocol design	10.1111/gcb.17031
Li, Shi, Li, Xiao, Song, Zhang, Wang, Gu, Liu, & Lai	2024	System design with case studies	Real-time carbon neutrality management	Proposed a ModelX + MRV + O system using IoT and blockchain for real-time carbon neutralization	Extends MRV toward continuous, auditable carbon-neutrality operations	10.1016/j.apenergy.2024.123763
Körner, Leinauer, Ströher, & Strüker	2025	Conceptual and systems-oriented analysis	Voluntary carbon markets / decarbonization	Framed digital MRV as a key enabler for scalable and credible decarbonization markets	Important conceptual reference for digital MRV architecture	10.1007/s12599-025-00953-3
Thornbush & Govind	2025	Systematic review	Dryland nations in the Global South	Reviewed MRV protocol challenges and improvement pathways for carbon trading in drylands	Valuable for adapting MRV to underrepresented geographies	10.3390/su17241100 1
Yao & Zhang	2025	Perspective / gap analysis	Land-based carbon dioxide removal	Showed how life cycle assessment can strengthen MRV but also highlighted methodological gaps	Useful for integrating LCA consistently into CDR crediting protocols	10.1021/acs.est.4c09510
Merlo, Mendonça, Santos, Carvalho, Guerra, & Brandão	2025	Literature review	Blockchain in carbon markets	Synthesized blockchain applications for registries, transparency, and verification in carbon markets	Helps position blockchain as an MRV-support technology rather than a standalone solution	10.1007/s44274-025-00260-4
Traub, Morillas, Gil, Álvarez, & Martínez	2025	Index development and reporting assessment	Corporate emissions disclosure	Introduced the Carbon Integrity Index to assess transparency and completeness of corporate carbon reporting	Useful for evaluating reporting quality within carbon accounting systems	10.3390/su17177628
Brown & MacAskill	2025	Review and trajectory analysis	City-level carbon emissions accounting	Examined how cities use carbon data and what limits advanced urban carbon accounting practice	Important for municipal carbon accounting and data-governance frameworks	10.1016/j.scs.2025.106677

Table S4. Integration of IoT, AI, and Carbon Accounting Systems.

Author(s)	Year	Methodology	Context	Key Findings	Implication	DOI
Woo, Fatima, Kibert, Newman, Tian, & Srinivasan	2021	Literature review	Building energy performance MRV and carbon credit markets	Blockchain can improve traceability, transparency, and trust in MRV workflows for building energy and carbon-credit systems	Foundational for digital MRV architectures that integrate monitored data with auditable carbon accounting	10.1016/j.buildenv.2021.108199
Xu, Tao, Das, Kwok, Liu, Kuan, Lau, & Cheng	2024	Framework development and case-oriented design	Construction material and product certification	Proposed a blockchain-based framework for carbon management and certification across construction materials/products	Supports verifiable product-level carbon accounting with interoperable digital records	10.1016/j.aei.2023.102242
Luo, Shen, Liang, Sun, & Dong	2024	System development and application case	Solar photovoltaic systems in Hong Kong buildings	Developed a solar-PV blockchain MRV tool for cleaner built-environment applications	Useful for tamper-resistant carbon accounting in distributed energy systems	10.1016/j.jclepro.2024.143456
Luo, Shen, Liang, Sun, & Dong	2024	Information-system design and application	Building life-cycle carbon auditing in Hong Kong	Built a traceable and immutable blockchain-enabled information management system for building life-cycle carbon MRV	Strengthens whole-life carbon accounting and regulatory reporting in buildings	10.1016/j.resconrec.2024.107736
Li, Shi, Li, Xiao, Song, Zhang, Wang, Gu, Liu, & Lai	2024	System design with applied modeling	Real-time carbon neutrality management	Proposed the **Modelx + MRV + O** system for real-time, credibility-oriented carbon neutrality management	Important example of integrating measurement, accounting, and operational decision support	10.1016/j.apenergy.2024.123763
Li, Jiang, Lin, Chen, Weng, & Jim	2025	Platform development and evaluation	Prefabricated building materialization	Developed an integrated **BIM-IoT** platform for real-time carbon-emission assessment and tracking	Shows how digital twins/BIM plus IoT can operationalize carbon accounting during construction execution	10.1016/j.resconrec.2025.108122
Aurangzeb & Yoon	2025	Proof-of-concept system	Sustainable construction processes	Proposed **AB-CELS**, integrating an AI-powered multimodal model with blockchain smart contracts to automate emissions ledger creation	Demonstrates AI-assisted parsing plus immutable carbon ledgers for auditable construction accounting	10.1016/j.autcon.2025.106286
Wu, Wang, He, & Chen	2025	Systematic review and framework proposal	Dynamic carbon monitoring in AEC	Reviewed real-time AEC carbon monitoring and proposed a framework combining sensors, BIM, RFID, and calculation layers	Useful for designing integrated monitoring-to-accounting systems in construction	10.1016/j.seta.2025.104289
Das	2025	Integrative review	Sustainable energy-efficient smart buildings	Reviewed how IoT and AI jointly support predictive maintenance, energy forecasting, climate control, and carbon reduction in smart buildings	Strong enabling reference for IoT-AI integration before formal carbon accounting layers are added	10.3390/su172210313
Xie, Li, Zaman, Song, & Wu	2026	Comprehensive review	GIS–AI-enhanced building LCA	Reviewed integration of GIS and AI within building life-cycle assessment and proposed a GIS–AI framework	Extends carbon accounting toward automated, spatially explicit, data-driven LCA systems	10.1016/j.enbuild.2026.117095
Pourrahmani, Talebi Amiri, Madi, & Owusu	2025	Review article	Carbon sequestration systems	Reviewed the joint use of IoT, AI, and blockchain for monitoring carbon fluxes, prediction, and transparent accounting/verification	One of the clearest direct integration studies across all three layers	10.1016/j.egyr.2025.05.042
Alotaibi, Khallaf, Abdallah, Zoubi, & Alnesafi	2024	Design-oriented framework study	Supply-chain ESG and carbon reporting	Developed a blockchain-driven framework for automated carbon accountability in supply chains	Relevant for extending IoT/AI-enabled enterprise data into trusted carbon reporting systems	10.3390/su16241872
Körner, Leinauer, Ströher, & Strüker	2025	Conceptual systems analysis	Digital MRV for decarbonization	Framed **digital MRV** (**dMRV**) as a scalable information-systems capability for decarbonization programs	Important theoretical anchor for integrating sensing, data exchange, verification, and reporting	10.1007/s12599-025-00953-3
Merlo, Mendonça, Santos, Carvalho, Guerra, & Brandão	2025	Literature review	Carbon markets	Reviewed blockchain applications in carbon markets, including verification, registries, and interoperability	Useful for positioning blockchain as an accounting and trust layer above emissions data systems	10.1007/s44274-025-00260-4
Boonrat, Wattanasoontorn, Ruktaengam, Boonmeeprakob, & Roswhan	2025	Pilot study using AI and big data	Tourism area carbon assessment in Phuket	Used AI object detection and electricity-use data to assess tourism-area carbon emissions	Demonstrates practical fusion of digital sensing/data streams with carbon estimation in urban services	10.3390/engproc2025108023
Li, Fei, Du, Ong, & Arisian	2024	Framework development	Maritime transport decarbonization	Proposed a near-real-time carbon accounting framework for shipping operations	Strong sectoral example of operational data feeding near-real-time carbon accounting	10.1016/j.tre.2024.103724
Li, Yang, Du, Liu, Zhang, Yang, Zhang, & Liu	2024	Review study	Electricity power industry	Reviewed direct and indirect carbon accounting approaches for the electricity industry	Important accounting-method reference for integrating digital power data with carbon models	10.1016/j.apenergy.2024.122681
Brown & MacAskill	2025	Analytical review	City carbon accounting and management	Examined trajectories toward advanced urban carbon-data use	Useful for situating integrated digital carbon systems at city scale	10.1016/j.scs.2025.106677
Pittri, Aklashie, Godawatte, Sackey, Agyekum, & Ghansah	2025	Systematic review	Construction industry	Reviewed how IoT supports carbon-emission management in construction	Good source on the sensing layer that feeds integrated construction carbon systems	10.3390/iic1030008
Cespedes-Cubides & Jradi	2024	Review article	Building operational stage	Reviewed digital twins for improving building energy efficiency	Supports the digital-twin layer that can combine IoT streams, AI analytics, and carbon indicators	10.1186/s42162-024-00313-7
Arsecularatne, Rodrigo, & Chang	2024	Review article	Building energy and digital twins	Synthesized how digital twins help reduce energy consumption in buildings	Relevant enabling study for carbon-aware building operation through digital replicas	10.3390/su16219275
Sandaruwan, Illankoon, & Yiu	2025	Review article	Embodied-carbon tracking in buildings	Reviewed technology-based embodied-carbon tracking and monitoring systems	Directly relevant to integration of digital technologies with embodied carbon accounting	10.3390/buildings15244421
Zhao, Li, Shen, Teng, Wu, & Liu	2025	Review article	Construction industry carbon management	Reviewed current status and emerging trends in managing construction carbon emissions	Strong synthesis of the wider ecosystem into which IoT/AI/accounting integration fits	10.1016/j.rser.2024.115237
Yang, Tang, Zhang, Zhang, & Doan	2024	Review article	Construction digital twins	Reviewed digital twin architecture, applications, trends, and challenges in construction	Supports integration pathways between physical sensing, analytics, and sustainability assessment	10.3390/buildings14092616
Zhao, Wu, Yu, Wang, & Huang	2025	Review article	Construction carbon accounting	Reviewed accounting scales, boundaries, trends, and gaps in construction carbon emissions	Useful for linking digital monitoring systems to appropriate accounting boundaries and scales	10.3390/buildings15111900

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