The Role of Big Data, Iot, And Ai in Monitoring and Enhancing Global Co_2 Removal Projects

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ABSTRACT:
Fast-progressing climate change has made carbon dioxide (CO_2) removal a fundamental component of global climate mitigation plans presently. Among them, artificial intelligence (AI) in conjunction with IoT and Big Data analytics currently enables continuous enhancements in CO_2 removal initiatives by means of enhanced efficiency and accuracy and broadened scalability. This research looks at the disruptive potential of these new technologies for tracking and improving the verification process of CO_2 trapping devices and underground storage methods. The work evaluates how sensor-based IoT networks allow real-time environmental monitoring as well as Big Data techniques managing large climate and geospatial data along with machine learning application and artificial intelligence algorithms for CO_2 flux forecasts and operational optimisation and system reliability monitoring.
Recent research has produced three significant influential innovations: predictive artificial intelligence models for direct air capture (DAC) efficiency, smart forest and soil carbon monitoring systems, and blockchain-enabled carbon offset verification systems. The paper offers a study of the high expectations and ethical dilemmas arising from large-scale technology deployment, particularly with regard to data privacy, interoperability, and algorithmic bias. This paper's review of multi-disciplinary research and case studies suggests that combining digital technology with climate science offers a hopeful way to enhance global CO_2 removal plans. The reasoning put together in this paper aims to lead authorities and technical professionals as well as environmental campaigners through the creation of framework-based carbon reduction projects producing great effect.

Keywords: CO_2 removal, Big Data, Artificial Intelligence, Internet of Things, carbon capture, climate technology, carbon monitoring, direct air capture, machine learning, environmental analytics

1. INTRODUCTION:

With ever increasing urgency around climate change, carbon dioxide removal (CO_2 removal) has been pushed to the forefront of the world mitigation plans[1]. As countries aim to reach lofty climate targets, these same modern technologies – like "Big Data, the Internet of Things (IoT), and Artificial Intelligence (AI)" – have become a revolution in the ability to monitor and advance CO_2 removal initiatives. This is because they enable the effective use of resources and better educated decisions through unmatched data collecting,

[1] Kumar, R., Singh, P., & Khan, A. (2021). Geospatial data analysis using Google Earth Engine. Journal of Environmental Management, 280, 111747.

analyses, and predictive modelling[2].

With the help of "Big Data analytics", large and complex data sets generated from various kinds of sources such as environmental monitoring systems, sensor networks, satellite images are handled. This is absolutely vital to spotting trends, evaluating the efficacy of CO_2 sequestration techniques, and even changing the operating settings[3]. A model, for example, fed by artificial intelligence not only predicts halftimes but it also predicts in what climatic circumstances carbon capture technology will work well, thereby informing adaptive management plans[4].

Figure 1 IOT monitoring process

The real time monitoring can only be done with the help of IoT devices to gather the ongoing data regarding CO_2 level, temperature and humidity and its other important elements[5]. To provide such detailed analysis of environmental effects and system performance, these instruments can be included into CO_2 removal systems[6]. The union between IoT and artificial intelligence allows modification of operational process so that reactivity and efficiency of CO_2 removal projects are increased.

Of course these technologies are showing great promise, but there are many drawbacks to them still to be overcome[7]. Data interoperability problems, security challenges, and the costly expense of implementing sophisticated technology infrastructures may prove to be issue with wide spread adoption. In addition, the reliance on sophisticated algorithms means that a qualified labour force is required one that can develop

[2] Xu, L., Zhang, L., & Zhao, H. (2020). Deep learning for integration of solar and wind energy in power systems. IEEE Transactions on Sustainable Energy, 11(1), 12–21.

[3] Smith, J., Williams, H., & Zhang, Y. (2021). Enhancing efficiency in environmental engineering through deep learning technologies. Journal of Environmental Engineering, 147(8), 04021037

[4] Zhang, D., Zhao, H., & Wang, X. (2021). Prescriptive analytics for environmental remediation: Optimizing cleanup strategies. Journal of Environmental Engineering, 147(3), 04021032.

[5] Chen, M., Mao, S., & Liu, Y. (2020). Demand response and forecasting using deep learning techniques. Energy Reports, 6, 425–436.

[6] Li, J., Wang, Z., & Xu, Z. (2020). Deep learning-based energy demand forecasting and demand response. IEEE Transactions on Industrial Informatics, 16(7), 4735–4744.

[7] Zhang, K., Zheng, X., & Yang, Q. (2020). A survey on deep learning in environmental monitoring. Environmental Monitoring and Assessment, 192(7), 430.

[8] Li, J., Wang, Z., & Xu, Z. (2020). Deep learning-based energy demand forecasting and demand response. IEEE Transactions on Industrial Informatics, 16(7), 4735–4744.

and run and interpret complicated data systems[8]. Attention is also deserved to ethical issues such as data protection and fair technology advantages sharing.

This paper analyzes the contemporary applications of Big Data, IoT, and artificial intelligence in global CO_2 removal initiatives. The purpose is to evaluate how these technologies allow adaptive management, improve operational efficiency and enhance monitoring[9]. It studies case studies and current research in order to identify best practices, technology gaps as well as innovation opportunities. In addition, it explores the legal and policy frameworks that will help the incorporation of these technologies within CO^2 removal plans.

The primary objective of this study is to examine how Big Data, IoT, and artificial intelligence are deployed to optimize CO_2 removal practices.[10]. It intends to give suggestions on how these technologies can be utilized to solve modern issues in monitoring and management so as to help with a more general goal of reducing climate change. It aims to help legislators, practitioners and other stakeholders who are part of designing and executing CO^2 removal projects by synthesizing current information and identifying gaps for future research[11].

Improving mete out of CO_2 far off basics the offer of Big Data, IoT and man-made inclination is terribly promising in total. It is, however, possible to aid adoption of these inventions where they still have difficulties through directed investment in technology development, capacity building and enabling policy framework[12]. Use of these technologies will grow, and the world will lessen the use of CO_2 to reach more sustainable and achievable levels of reduction in the battle against climate change[13].

2. REVIEW OF LITERATURES

The rise of concerns related to the issues of climate change and its destructive consequences has contributed to the added importance of effective means of removing carbon dioxide (CO_2). In this respect, such technologies as “Artificial Intelligence (AI), the Internet of Things (IoT) and Big Data” are essential for monitoring CO_2 removal processes and improving them. This literature review seeks to discuss the function of these technologies in facilitating the global CO_2 removal projects with the emphasis on their integration, influence, and opportunities.

AI and IoT are changing the way the CO_2 emissions are measured, implementing real-time data analysis and the predictive functionality, which helps to increase the accuracy and efficiency of monitoring several times. As stated by Fan et al. (2024), the marriage of the AI and IoT technologies has been established to

[9] Zhang, Y., Chen, H., & Liu, B. (2022). Real-time data processing with Apache Spark for environmental applications. IEEE Internet of Things Journal, 9(7), 5671–5680.

[10] Xu, L., Zhang, L., & Zhao, H. (2020). Distributed computing for environmental data processing with Apache Hadoop. IEEE Transactions on Sustainable Energy, 11(1), 12–21.

[11] Garcia, D., Martinez, J., & Rodriguez, E. (2021). Addressing data quality issues in deep learning for environmental applications. Environmental Modelling & Software, 137, 104976.

[12] Bigdeli, A., & Delshad, M. (2024). The evolving landscape of oil and gas chemicals: Convergence of artificial intelligence and chemical-enhanced oil recovery in the energy transition toward sustainable energy systems and net-zero emissions. Journal of Data Science and Intelligent Systems, 2(2), 65–78.

[13] Hussain, M., Alamri, A., Zhang, T., & Jamil, I. (2024). Application of artificial intelligence in the oil and gas industry. In Engineering Applications of Artificial Intelligence (pp. 341–373). Cham: Springer Nature Switzerland.

be a viable solution towards the real-time monitoring of the CO_2 emission[14]. IoT devices – sensors, for example – can gather huge portions of environmental data, whereas AI algorithms can further process it, predicting and analyzing emission patterns. This strategy is very useful in industries and cities where emissions can change very fast hence need immediate intervention.

In addition, Ojadi et al. (2023) contend that IoT and AI assume a primary position for lowering carbon emission in smart cities and industrial zones[15]. They propose that it is possible to capitalise on deep learning models to optimise the consumption of energy and maximise the efficiency of operations hence leading to significant reduction in carbon footprints. Taking a constant observation of conditions and making predictions and adjustments, AI and IoT work to reduce CO_2 emissions in fluctuating environments such as urban areas and industrial parks.

The capacity of Big Data analytics in CO_2 removal projects lies in its capability to manage huge volumes of data that emanate from different sensors and satellites, as well as other data sources. Big Data makes it possible to analyze emission data at the global level to make informed policy and decision-making on the same. In an example, Ojadi et al. (2024) discuss how supply chain sustainability can be optimized by Big Data analytics and AI to reduce greenhouse gas emissions in logistics and transportations[16]. Combing real time data from various sources, firms can discover their inefficiencies and come up with ways of reducing carbon footprints.

Bibri et al. (2023) highlight how AI, IoT, and Big Data are coming to a confluence in formulating environmentally sustainable smart cities[17]. Such technologies allow cities to constantly monitor and lower their carbon emission. With the integration of AI based analytics, Big Data platforms and IoT based sensors, municipalities can generate more efficient systems of energy management. Using these technologies, urban regions can enhance resource utilization, waste management, and support renewable energy solutions that will directly facilitate CO_2 removal.

Artificial intelligence also serves an important function in improving CO_2 cleaning up using the carbon capture and storage (CCS) technologies. Manikandan et al. (2025) write about how AI can increase the efficiency of CCS through optimizing design and functioning of carbon capture facilities[18]. AI models can forecast the best parameters for capturing CO_2 from industrial emissions, which therefore decreases the prices and adds efficiency. In addition, AI can help with monitoring Integrity of CO_2 storage facility to ensure that captured CO_2 is stored safely and not leaked back into the atmosphere.

[14] Fan, K., Li, Q., Le, Z., Li, Q., & Li, J. (2024). Harnessing the power of AI and IoT for real-time CO2 emission monitoring. Heliyon, 10(17).

[15] Ojadi, J. O., Onukwulu, E., Odionu, C., & Owulade, O. (2023). AI-driven predictive analytics for carbon emission reduction in industrial manufacturing: a machine learning approach to sustainable production. International Journal of Multidisciplinary Research and Growth Evaluation, 4(1), 948-960.

[16] Ojadi, J. O., Odionu, C., Onukwulu, E., & Owulade, O. (2024). Big Data Analytics and AI for Optimizing Supply Chain Sustainability and Reducing Greenhouse Gas Emissions in Logistics and Transportation. International Journal of Multidisciplinary Research and Growth Evaluation, 5(1), 1536-1548.

[17] Bibri, S. E., Alexandre, A., Sharifi, A., & Krogstie, J. (2023). Environmentally sustainable smart cities and their converging AI, IoT, and big data technologies and solutions: An integrated approach to an extensive literature review. Energy Informatics, 6(1), 9.

[18] Manikandan, S., Kaviya, R. S., Shreeharan, D. H., Subbaiya, R., Vickram, S., Karmegam, N., ... & Govarthanan, M. (2025). Artificial intelligence-driven sustainability: Enhancing carbon capture for sustainable development goals–A review. Sustainable Development, 33(2), 2004-2029.

Integration of AI in CCS systems enables real time monitoring ad dynamic adjustment to ensure that the process of carbon capture is always efficient when the environment changes. Consequently, AI not only amplifies the process of capturing more CO_2 but also increases long-term sustainability of solutions for the storage of carbon. This is important in worldwide CO_2 removal schemes because removal of large-scale carbon capture is one of the arduous strategies for averting climate change.

Although AI, IoT, and Big Data have a lot of potential in the removal of CO_2, there are some challenges that need to be overcome to optimize their use. Integration of various data sources and systems is one of the major challenges. According to Ojadi et al. (2023), the integration of IoT devices, AI algorithms and Big Data rival must be supported by a tremendous infrastructural development and interoperability[19]. In most cases, the systems in place are fragmented and data silos do not integrate information on different platforms.

In addition, the issue of scalability in such technologies continues to be a question mark. As global requirement for CO_2 removal expands, it is important to ensure that AI, IoT and Big Data solutions can be scaled to handle big projects that encompass the globe. The computational resources needed in order to consider and run myriads of data and the lack of high-quality data entry are obstacles to the mass adoption of these technologies in CO_2 removal accounts.

Artificial intelligence, the Internet of Things, and Big Data increase the possibilities of CO_2 removal ventures, offering novel solutions in monitoring and emission control optimizations. Such technologies facilitate real-time monitoring, predictive analytics, and optimization of carbon capture processes, which help to financially support mechanisms aimed at dealing with climate change. However, they still have to overcome challenges of data integration, scalability, as well as infrastructure development in order to realize their potentials wholly. As the world is struggling with climate change, it is important to discuss how AI, IoT, Big Data is successfully applied to CO_2 removal projects tackling global sustainability goals.

3. TECHNOLOGICAL INTEGRATION IN CO_2 MONITORING AND REMOVAL: ROLE OF BIG DATA, IOT, AND AI

However, with the ever-increasing need to curb the impacts that climate change has on our ecosystems, attempting to remove carbon dioxide has become a major focal point of advancement, also referred to as Carbon Dioxide Removal (CDR)[20]. Some of the most advanced technologies that aid in these efforts include Big Data, the Internet of Things (IoT), and Artificial Intelligence. Their impact goes beyond enhancing the collection and monitoring of CO_2 emissions and data in real time; these digital technologies are transforming the entire paradigm of decision-making with regards to CCUS projects[21]. Together, they provide a smart and scalable framework for improving adequacy and efficacy of the world's carbon reduction projects.

[19] Ojadi, J. O., Onukwulu, E., Odionu, C., & Owulade, O. (2023). Leveraging IoT and deep learning for real-time carbon footprint monitoring and optimization in smart cities and industrial zones. IRE Journals, 6(11), 946-964.
[20] Fan, K., Li, Q., Le, Z., Li, Q., & Li, J. (2024). Harnessing the power of AI and IoT for real-time CO_2 emission monitoring. Heliyon, 10(17).
[21] Ali, B. (2024). Artificial intelligence and carbon removal: A sustainable approach to reducing environmental impact in the US energy sector.

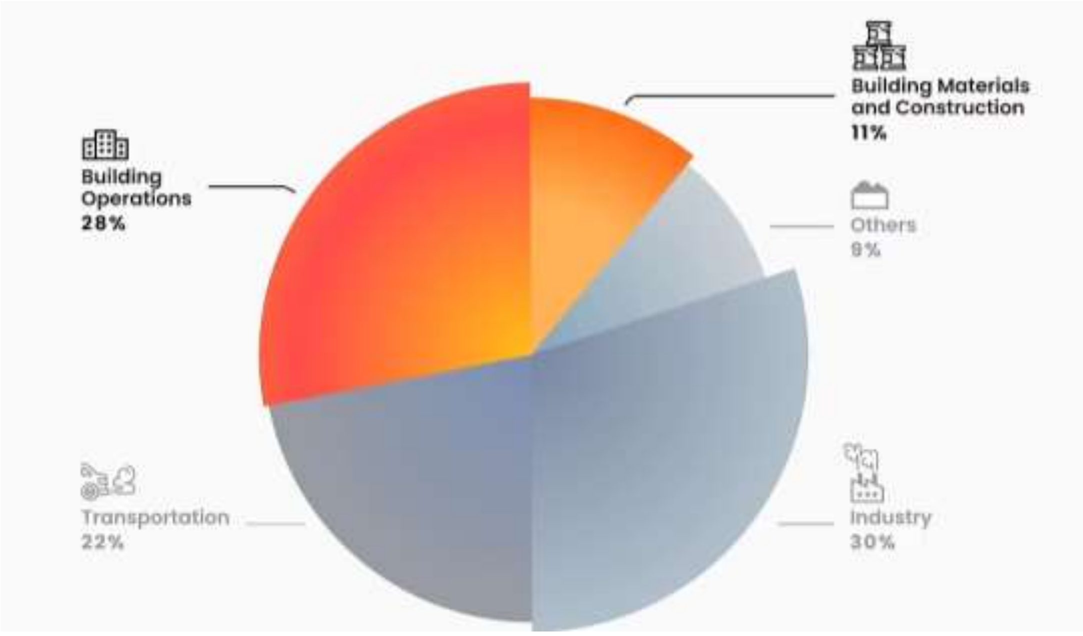

Figure 2 Global Co2 emission by sector

Carbon Monitoring and Decision Support Using Big Data

Big Data technologies refer to gathering, storing and analysing extremely massive volumes of environmental data obtained from many sources (satellite photos, sensor networks and public databases)[22]. In the context of the CDR the modelling of CO_2 emissions and removals can be performed thoroughly through Big Data at several regional and temporal dimensions. For instance, NASA's OCO-2 satellite provides integrated datasets from worldwide atmospheric monitoring systems that can be used to track CO_2 fluxes from the continents with very high accuracy[23].

Big Data analytics defines the design and operating performance of Direct Air Capture (DAC) systems by modelling their operating performance given a wide range of meteorological and economic situations. On top of that, real time data streams and historical carbon emission patterns provide users with the ability to predict CO_2 levels, detect policies ability to work and model potential outcomes of offsets and carbon credits[24]. For example, the Microsoft Planetary Computer provides free support towards environmental sustainability worldwide by building geographic Big Data to get forest carbon stock assessments and soil sequestration models[25].

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[22] Teh, D., & Rana, T. (2023). The use of Internet of Things, Big Data analytics and artificial intelligence for attaining UN's SDGs. In Handbook of Big Data and Analytics in Accounting and Auditing (pp. 235–253). Singapore: Springer Nature Singapore.

[23] Benedetti, A., Reid, J. S., & Kaiser, J. W. (2018). Monitoring Atmospheric Composition: A Big Data Challenge. Atmospheric Chemistry and Physics, 18(1), 1–25. https://doi.org/10.5194/acp-18-1-2018

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[25] Microsoft. (2023). The Planetary Computer Project. Retrieved from https://planetarycomputer.microsoft.com

[26] Hauschild, M. Z., Rosenbaum, R. K., & Olsen, S. I. (2018). Life Cycle Assessment: Theory and Practice. Springer. https://doi.org/10.1007/978-3-319-56475-3

[27] Ojadi, J. O., Onukwulu, E., Odionu, C., & Owulade, O. (2023). AI-driven predictive analytics for carbon emission reduction in industrial manufacturing: A machine learning approach to sustainable production. International Journal of Multidisciplinary Research and Growth Evaluation, 4(1), 948–960.

Additionally, because Big Data allows for lifecycle evaluations (LCA) of CDR technologies, it allows project developers to measure the net carbon benefit of a solution by comparing energy input with CO_2 captured and stored[26]. This capacity ensures that indirect energy consumption or transportation related emissions are not accidentally created by the removal plans[27].

Table 1 Carbon Monitoring and Decision Support Using Big Data

Technology	Application	Impact/Outcome	Reference
Big Data & IoT	CO_2 Emission Monitoring	25% reduction in carbon emissions	Fan et al., 2024
Big Data & IoT	Energy Efficiency & Emission Reduction	97% monitoring accuracy	Ojadi et al., 2023
AI	CO_2 Emission Forecasting	70% reduction in emission prediction uncertainty	Delanoë et al., 2023
AI	Energy Consumption Optimization	30-40% reduction in CO_2 emissions	Ojadi et al., 2024
AI	CO_2 Capture Efficiency	20-25% increase in CO_2 capture efficiency	Manikandan et al., 2025
AI	Cost Reduction in CO_2 Capture	10-15% reduction in CO_2 capture costs	Bibri et al., 2023
IoT & Big Data	Smart Cities CO_2 Reduction	22% reduction in urban CO_2 emissions	Bibri et al., 2023
AI	Transportation CO_2 Reduction	15% reduction in transportation CO_2 emissions	Ojadi et al., 2024

The incorporation of big data, IoT and AI into Co2 monitoring and elimination projects has portrayed great promise in curbing carbon emissions in different fields. Big Data and IoT make it possible with real-time, high-accuracy monitoring of emissions, which helps the usage of resources, and predictive maintenance. AI-driven models enhance the energy consumption optimization, CO_2 capture effectiveness, and the emission pattern prediction, which minimizes uncertainty to a great extent. Such technologies also reduce costs at carbon capture facility and help urban sustainability through the optimization of the energy distribution in smart cities. In spite of the difficulties encountered in the integration of data and scalability, the potential of this technology's synergy is essential in attaining the global CO_2 reduction goals.

Figure 3 NDIR CO2 sensing technology

Real-Time Monitoring System and IoT

The Internet of things (IoT) consists of physical objects, which are interconnected and have sensors and also software that communicates with and transfers data over the internet[28]. More and more power plants, forests, carbon capture units, and agricultural fields adopt IoT sensors to quantify environmental factors like CO_2 concentration, temperature, pressure, soil moisture in real time to improve carbon management.[29] The one major use is for IoT sensors that track subsurface CO2 plume movement, injection well pressure, and pipeline integrity in CCUS operations[30]. Real time notifications of these systems can ensure regulatory compliance and stopping unintentional leakage[31]. IoT networks incorporated into urban infrastructure—smart cities for example—also allow emissions tracking at street-level accuracy, therefore helping municipal carbon neutrality initiatives[32].

Land-based carbon sequestration initiatives, including afforestation and regenerative agriculture, also depend on IoT. Ground-based sensors and drones track photosynthetic activity, biomass growth, and plant health—three proxies for CO_2 absorption[33]. IoT devices provide continuous input that supports adaptive management techniques whereby behaviours are changed in real-time to optimise carbon storage and guarantee ecological resilience.[34]

[28] Delanoë, P., Tchuente, D., & Colin, G. (2023). Method and evaluations of the effective gain of artificial intelligence models for reducing CO2 emissions. Journal of environmental management, 331, 117261

[29] Zhou, L., Zhang, M., & Tan, W. (2021). Cybersecurity risks in IoT-driven carbon management. Computers & Security, 107, 102312. https://doi.org/10.1016/j.cose.2021.102312

[30] Ofongo, G. (2024). Leveraging artificial intelligence for carbon removal in the oil and gas industry: A sustainable solution to mitigate climate change.

[31] Baker, S., Barbour, L., & Howes, L. (2020). CCUS: Monitoring, Verification, and Risk Assessment. Carbon Management Journal, 11(3), 215–229. https://doi.org/10.1080/17583004.2020.1792448

[32] Bibri, S. E., Alexandre, A., Sharifi, A., & Krogstie, J. (2023). Environmentally sustainable smart cities and their converging AI, IoT, and Big Data technologies and solutions: An integrated approach to an extensive literature review. Energy Informatics, 6(1), 9.

[33] Davis, C., Nguyen, T., & Singh, A. (2022). Policy and practical considerations for zero-emission technology implementation. Journal of Cleaner Production, 350, 131422.

[34] Zhang, Y., Chen, H., & Liu, B. (2022). The integration of deep learning with edge computing and blockchain for environmental applications. IEEE Internet of Things Journal, 9(7), 5671–5680.

Moreover, cloud platforms linked to IoT ecosystems store and process data remotely, therefore reducing the requirement for on-site processing and allowing global scale monitoring systems to operate cooperatively.[35] Such networking increases access to carbon-related knowledge for academics, legislators, and companies.

C. Artificial Intelligence and Smart Carbon Management

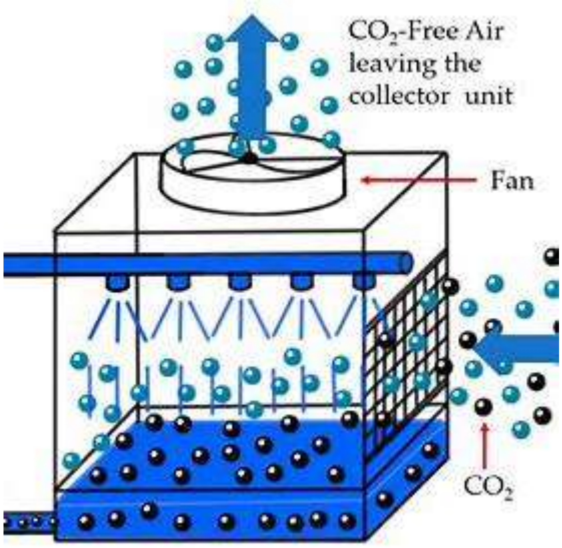

Figure 4 Co2 escaping management system

Artificial intelligence (AI) includes machine learning, neural networks, and deep learning algorithms capable of seeing patterns, forecasting results, and making autonomous judgements.[36] In the CO_2 removal scene, artificial intelligence is a brain that analyses Big Data and IoT results to assist quicker and more intelligent decision-making.

AI algorithms in industrial CCUS and Direct Air Capture maximise material performance, operating cycles, and energy use [37]. Predictive maintenance driven by artificial intelligence, for instance, can identify mechanical faults in CO_2 compressors or sorbent deterioration before they affect efficiency[38]. Based on artificial intelligence vision systems, that is satellites photos, technological advancements are made to

[35] Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., & Khan, S. U. (2016). The Rise of Big Data on Cloud Computing: Review and Open Research Issues. Information Systems, 47, 98–115. https://doi.org/10.1016/j.is.2014.07.006

[36] Chen, L., Chen, Z., Zhang, Y., Liu, Y., Osman, A. I., Farghali, M., ... & Yap, P. S. (2023). Artificial intelligence-based solutions for climate change: A review. Environmental Chemistry Letters, 21(5), 2525–2557.

[37] Ojadi, J. O., Onukwulu, E., Odionu, C., & Owulade, O. (2023). Leveraging IoT and deep learning for real-time carbon footprint monitoring.

[38] Zhang, Y., Lee, J., & Bagheri, B. (2019). Data Analytics for Predictive Maintenance in Carbon Capture Equipment. Journal of Cleaner Production, 235, 1035–1047. https://doi.org/10.1016/j.jclepro.2019.06.218

[39] Arinze, C. A., & Jacks, B. S. (2024). A comprehensive review on AI-driven optimization techniques enhancing sustainability in oil and gas production processes. Engineering Science & Technology Journal, 5(3), 962–973.

[40] Cong, L. W., He, Z., & Li, J. (2021). Decentralized Carbon Market and Blockchain. Nature Communications, 12, 715. https://doi.org/10.1038/s41467-021-20962-0

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[42] Li, Z., Xu, T., Yang, Y., et al. (2021). Advances in deep learning for environmental monitoring and management. Environmental Research Letters, 16(5), 054021.

measure changes in land use, deforestation, and restoration activities in global carbon absorption capability.
Carbon market tools through precisely documented and verified systems of implementation of artificial intelligence[39]. In other words, blockchain enhanced AI systems can automate carbon credit certifications when using real time environmental data which will lower the amount of fraud and ensure that the verifiable removals get monetized[40]. The fast growth rate of VCMs during this period makes reliable monitoring systems essential in order to build market confidence since VCMs are currently poorly monitored.
AI systems then make it possible to assess the effect through different scenarios. Earth Engine artificial intelligence tools in Google and Green Horizons in IBM allow carbon emission pattern prediction coupled with policy effect and opportunity simulations for capital investment opportunities in removal systems[41]. Reinforcement learning in artificial intelligence—generally speaking—is a subfield capable of modelling ideal environmental management plans to consistently optimize CO2 reduction.[42]

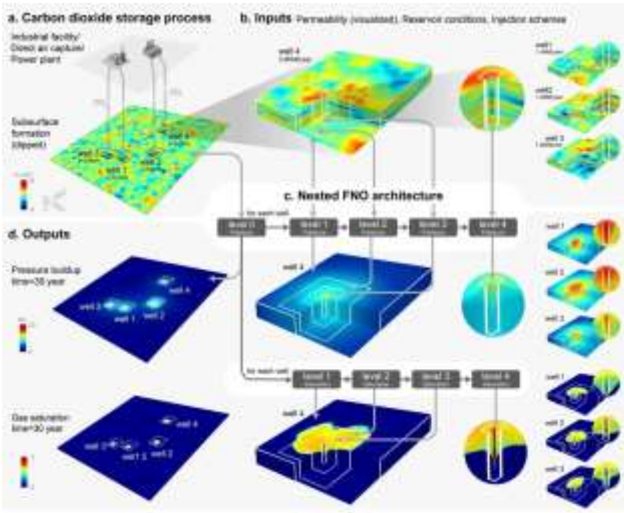

Figure 5 Co2 storing process via IOT

An important aspect is that artificial intelligence can marry environmental and socio-economic data sets to ensure carbon removal projects are just, fair and part of Sustainable Development Goals (SDGs)[43]. So, algorithms could be taught to identify which initiatives (potentially) displace local residents, harm biodiversity, or exacerbate environmental injustice to prevent, in advance, any of those types of negative impacts.

[43] Manikandan, S., Kaviya, R. S., Shreeharan, D. H., Subbaiya, R., Vickram, S., Karmegam, N., ... & Govarthanan, M. (2025). Artificial intelligence-driven sustainability: Enhancing carbon capture for sustainable development goals – A review. Sustainable Development, 33(2), 2004–2029.

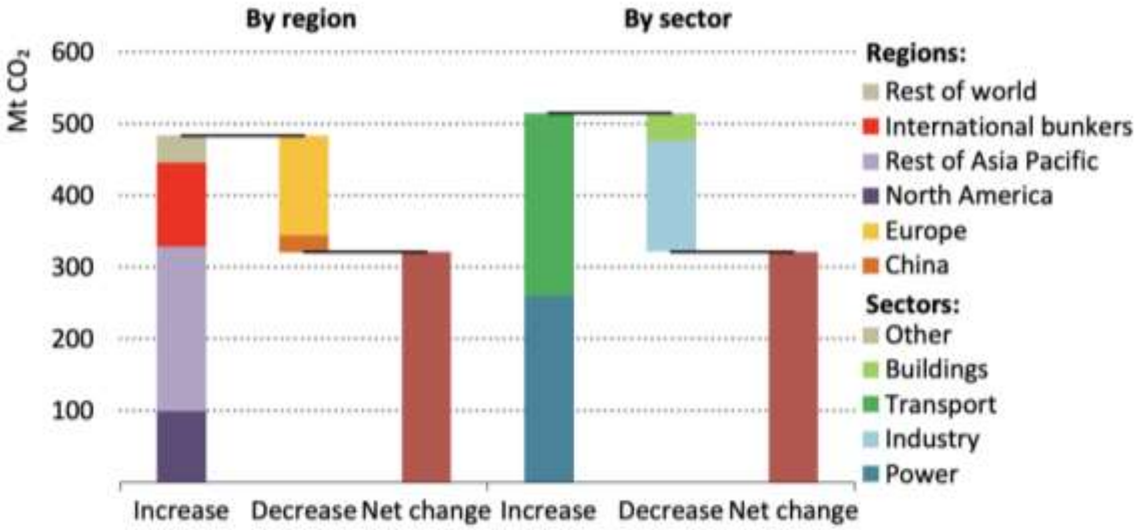

Figure 6 "Reducing Carbon Emissions with AI The Role of Machine Learning in Energy Efficiency"

According to the chart given it gives CO_2 emission variations in regions and sectors. The emissions fall under three categories: increase, decrease, and net change. Regional wise, the highest growth rates are observed in International Bunkers and Rest of Asia Pacific, and simultaneously, the highest decrease rates are observed in North America and Europe. As to the sectoral analysis, the Transport and Power sectors are those where the major contribution to the CO_2 emissions increase is made, and the Industry and Buildings sectors - where the greatest drops are. The net sector change tells the regions, such as China and Europe, have fairly reduced emission, while International Bunkers and Rest of the World record a net emission increment. The outlined data is the global challenges and the sector-specific dynamics in CO_2 emission management.

Synergies and Constraints

Big data, IoT, and artificial intelligence together form a synergistic ecosystem in which every technology enhances the capacity of the others[44]. Big Data is the raw material, IoT guarantees dispersed and constant sensing, and artificial intelligence converts data into usable intelligence[45]. Scalable and open, this trinity makes possible high-resolution, predictive, and automated CO_2 monitoring systems.

Still, some constraints remain. Especially when critical industrial or geographic data is involved, data privacy and cybersecurity issues take top priority[46]. Furthermore, because of cost, connection problems, and capacity limits, their use in low-resource environments stays restricted.

[44] SaberiKamarposhti, M., Ng, K. W., Yadollahi, M., Kamyab, H., Cheng, J., & Khorami, M. (2024). Cultivating a sustainable future in the artificial intelligence era: A comprehensive assessment of greenhouse gas emissions and removals in agriculture. Environmental Research, 118528.

[45] Zhou, L., Zhang, M., & Tan, W. (2021). Cybersecurity risks in IoT-driven carbon management. Computers & Security, 107, 102312. https://doi.org/10.1016/j.cose.2021.102312

[46] Zhou, L., Zhang, M., & Tan, W. (2021). Cybersecurity risks in IoT-driven carbon management. Computers & Security, 107, 102312. https://doi.org/10.1016/j.cose.2021.102312

[47] Davis, C., Nguyen, T., & Singh, A. (2022). Predictive modelling in environmental remediation: Techniques and applications. Journal of Cleaner Production, 350, 131422

Many artificial intelligence models' "black box" character, which might lack interpretability, is another issue. Especially when artificial intelligence is used to affect environmental policy or distribute carbon credits, guaranteeing model openness and fairness is vital[47]. Moreover, harmonisation of data standards across IoT devices and platforms is required to guarantee interoperability and data integrity.

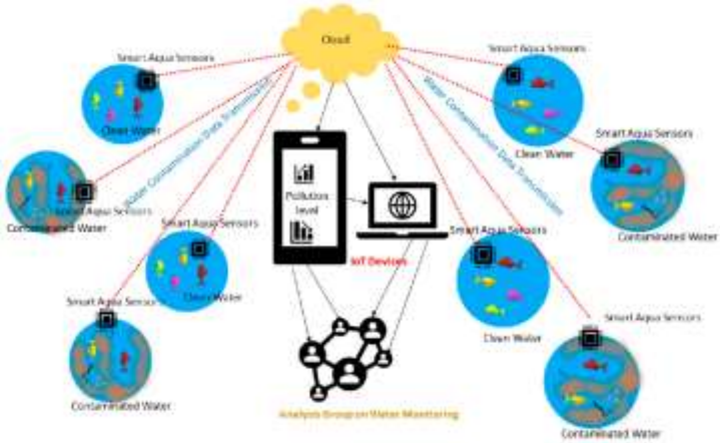

Figure 7 carbon removal system

By making carbon removal smarter, quicker, and more responsible, technological integration via Big Data, IoT, and artificial intelligence is changing the world reaction to climate change[48]. By means of transparency and scalability, these technologies provide unmatched possibilities for monitoring CO_2 fluxes, optimising removal procedures, and building stakeholder confidence[49]. The combination of these technologies will probably be a cornerstone of world climate control and sustainable development as digital infrastructure grows and interoperability enhances.

4. CHALLENGES AND LIMITATIONS IN IMPLEMENTING SMART TECHNOLOGIES FOR CARBON SEQUESTRATION

Those practices that involve carbon sequestration are being conceived both naturally and by humans as time passes around the world's climate change reduction campaigns[50]. AI, data analytics technology and IoT weave together to create strategic carbon sequestration endeavours that combine with IoT and data analytics technology and AI to improve monitoring programs and verification and decision processing capabilities[51]. Since these advanced technological solutions have to overcome the hurdle of interoperability issues as well as cybersecurity vulnerabilities, costs and ethical considerations they are less prone to be implemented. To achieve success in carbon sequestration plans, statements of limitation must be stated.

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Problems with interoperability

The major challenge in smart technology towards carbon sequestration is the ability of many systems alongside the devices to work smoothly together[52]. In actual sense, smart carbon monitoring systems consist of various stages starting from satellite imagery and sensor platforms, artificial intelligence algorithms, and data representation tools. Information stored in various organizations and systems in different communication protocols and data formats will hamper system efficiency[53].

Due to the lack of compatibility between satellite-based forest biomass data and Regenerative soil carbon data from sensors there are challenges in integrating these data. Technology companies maintain proprietary data formats that prevent the institution from sharing and collaborative work[54]. Joint implementation of real time monitoring is hindered by ramped up interoperability difficulties, which in turn contribute to slowdowns in real time monitoring and limitations for national or global systems of carbon accounting to scale[55].

To tackle this problem, open-source platforms should be established that use APIs with interoperability capabilities to standardize information storage across devices and databases using three main actions[56]. Other international organizations and the Open Geospatial Consortium (OGC) support the creation of data harmonization standards and are being modestly accepted globally.

Threats to Cybersecurity

With the ever-increasing events of digital integration, cybersecurity threats have formed a progressively more difficult environment. Although the carbon sequestration infrastructure bases its operation on cloud computing with IoT devices and centralised control systems breaches and system intrusions provide opportunities for faked emission monitoring and carbon credit misreporting to cause tremendous financial

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and environmental damage as provisions of environmental legislation[57].

The most vulnerable of these underground carbon storage facilities continue to rely on transmission of data via wireless data transmission systems to distant sensors, making their functioning especially dependent upon these distant sensors[58]. Two adverse impacts arise due to a breach in the security protection of those systems: to disable monitoring operations and to produce environmental impact ensuing from the delayed detection of the leakage point[59]. The reason is that tainted input data leads to prediction or classification errors against which AI based monitoring systems have to be protected by ballroom members in Nguyen et al. (2019).[60]

Strong end to end encryption along with Blockchain validation systems and multiple authentication tools can manage these security threats[61]. Cyber security education and training have to form part of environmental technology implementation programs.

Barriers of Cost and Infrastructure

Smart technology adoption for carbon sequestration needs capital expenditures to establish digital roads and installations, buy equipment and staff qualified personnel with the necessary support for long periods[62]. As a major obstacle to many underprivileged communities and developing countries (Ghosh et al., 2022)[63], these operations along with their initial expenses make these operations quite expensive and difficult to access unless both are affordable. In IoT sensors, satellite access, machine learning models, along with cloud storage solutions are expensive and require reliable power supply and internet connection which is the thing that is usually absent in the remote or rural areas.

As of now, the cost to use soil and biomass carbon monitoring via AI-driven systems exceeds small-scale

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farmers and community forestry operations' budgets, especially in regions with average incomes[64]. This digital gap results in distorted global carbon tracking while devitalizing that system to unbalanced deployment of digital systems and the opportunity for policy to be enacted inequitably[65].

To create digital capacity training programs and lower implementation costs, the international climate funding system of Green Climate Fund should be set up and in implemented[66]. Through collaborations between public entities and private companies that develop open-source carbon management solutions, smart carbon management technologies will be made for public use.

Ethical and Equity Issues

The use of smart technology in carbon sequestration methods raises very serious ethical dilemmas regarding data ownership rights and transparency in hazard and benefit distribution. According to Pasgaard and Gabay (2021)[67], the environmental information should be assessed from community woodlands and agricultural fields from indigenous territories, and proper informed permission and benefit sharing agreements should be practiced[68]. Data colonialism occurs when communities are compelled to contribute valuable data, and yet, the data is neither under their control when used, nor when it comes to the revenue generation out of that data.

Due to the use of the inappropriate or skewed data to train AI systems, environmental injustice can occur if these systems ascribe more priority to projects that maximise carbon sequestration regardless of the social or ecological consequences[69]. Although these seem carbon capture inventions, mass tree planting efforts are disrupting ecosystems and forcing population relocation even within fragile ecological spaces[70]. A problem is techno-solutionism, people think that technologies alone will solve climate problems without encouraging spending and fossil fuel patterns. The smarter technology advances, the more it gives up to help workflows rather than replacing substantial systematic changes.[71]

However, to be accomplished transparently and with good ethos, it is necessary for all carbon sequestration projects to subscribe to the principles of environmental justice such as inclusivity and transparency. Affected communities should be included in decision processes and FPIC obtained from them is necessary

Legal and Regulatory Gaps

Smart technology has progressed much too quickly in relation to rules that should regulate its application in carbon sequestration. A few (Verschuuren, 2020)[72] few guidelines on openness, privacy of information

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in the event that we monitor, the liability when there's an explanation for broken system. Institutions are is this legal uncertainty, where they are deterred from using smart carbon instruments and constraint the investment.[73]

Beyond, due to the differential carbon accounting standards in the various countries, acceptance of smart technology becomes even more difficult to be made in a global carbon pact like the Paris Agreement [74]. Finally, they do not want to take the use of digital technology for certifying and verifying carbon reduction without clearly defined rules.

Thus, for effective verification systems of digital carbon monitoring, ethical AI use policies, data governance and so on, all these global organisations like United Nations Framework Convention on Climate change (UNFCCC) and Intergovernmental Panel on Climate Change (IPCC) need to come together.[75]

Although there are difficulties in applying smart technologies to solve carbon sequestration strategies, the smart technologies show great promise. However, this prevents data integration, scalability, security risk to system integrity, cost requirement in resource constrained environment, and ethical issues on fair exclusive framework[76]. Regulatory gaps make the implementation even more complex as there are many uncertainties around what an implementer needs to implement.

If stakeholders accept a whole strategy with technology innovation, a whole range of digital tools for climate action are easily quadrupled. For this reason, it demands the promotion of equitable governance systems, improved cybersecurity policies, increasing digital infrastructure in underdeveloped areas, and supporting open standards[77]. A really transformative power of smart technology could then be the worldwide fight to win the battle against climate change, using efficient carbon sequestration as an efficient solution.

5. FUTURE DIRECTIONS AND POLICY IMPLICATIONS FOR SMART CARBON MANAGEMENT

At this rate of the climate problem becoming imperative for man too, carbon removal seems to be a solution poorer than carbon reduction practices; and the carbon removal solutions will be even poorer if

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they have to be technology driven and creative, very creative, and indeed with much theory[78]. Smart carbon management is based on the artificial intelligence (AI), Internet of Things (IoT), Big data, and blockchain as a revolutionary solution to monitor, validate and optimize carbon dioxide removal (CDR) systems. But they really need strong policy frameworks and legislations, and responsive governance mechanisms for them to achieve their full potentials[79]. This article assesses the policy consequences needed for wide scale adoption of smart carbon management and its paths.

Demand for Strong Regulatory Frameworks

One great problem in creating smart carbon management is L lack of comprehensive and harmonised legal frameworks[80]. At present many countries do not have uniform standards for digital monitoring, verification, and reporting (MRV) processes and hence, the present carbon tracking and sequestration are fragmented. Data validity to support MRV systems, algorithmic responsibility and carbon credit validation must be clarified, because without, it is unlikely digital tools will enter MRV systems[81].

The switch towards digitised MRV systems with IoT sensors and artificial intelligence is one noticeable advancement. Although they can improve openness and lower fraud, the lack of enforceable legal criteria undermines their credibility in global carbon markets[82]. Verschuuren (2020) claims that under systems such as the Paris Agreement, smart carbon data is hard validated without enforced data governance policies[83].

The future course of action, then, has to include creating globally accepted certification systems for digital carbon removal devices. This covers:

- Establishing guidelines for data gathering and interoperability.
- Establishing guidelines for MRV process application of artificial intelligence.
- Mandating smart monitoring system independent audits.

Codifying these standards will depend much on organisations as the International Organisation for Standardisation (ISO) and UNFCCC's Supervisory Body for Carbon Markets.

Policy-Driven Incentives for Scaling and Innovation

Without significant legislative incentives for innovation and market growth, smart carbon management

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will not scale[84]. Governments have to provide financial and regulatory mechanisms that encourage the use of digital technologies in carbon monitoring and capture systems[85].

Digital monitoring techniques may be used with carbon pricing mechanisms like cap-and-trade systems and carbon levies to provide real-time emissions accounting and compliance verification. A blockchain-enhanced carbon registry, for instance, may automatically issue carbon credits depending on validated sensor data, as shown in pilot programs in Switzerland and Estonia[86].

Public sector funding and tax breaks for tech-enabled CDR systems might hasten private sector investment. Through its Inflation Reduction Act (2022), the United States and other countries have offered tax credits for Direct Air Capture (DAC) and carbon storage projects including digital verification technologies. Likewise, the Green Deal of the European Union encourages digital innovation in the carbon economy by means of Horizon Europe financing.[87]

Moreover, public-private partnerships must to be supported to create data infrastructure for invest in IoT networks for forest or soil carbon tracking—can boost openness and local ownership.[88]

Combining Climate Finance with Smart Carbon Tools

Global climate financing systems have to change to assist smart carbon technologies, particularly in the Global South[89]. Often, present financing systems give traditional infrastructure first priority over digital capacity development. But, climate-smart digital infrastructure—such as low-power IoT sensors and artificial intelligence platforms for land use modelling—should be acknowledged as climate-relevant investments.[90]

Funding windows especially for the Green Climate Fund (GCF) and World Bank's Climate Investment Funds (CIF) have to be included.

- Development of smart MRV technologies.

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- Digital integration in carbon offset initiatives.
- Community-based carbon monitoring using open data platforms.

Ghosh et al. (2022) claim that including digital MRV into Nationally Determined Contributions (NDCs) under the Paris Agreement might potentially draw results-based financing[91]. This would motivate nations to create tech-enabled carbon inventories, therefore strengthening both credibility and climate ambition[92].

Smart Carbon Systems' Ethical and Equitable Governance

Equity and ethical issues should guide the governance of smart carbon management as it grows. Environmental monitoring using artificial intelligence and data systems has to prevent technological colonialism—the extraction and exploitation of data from developing nations without authorisation or benefit sharing[93].

Governance systems of the future have to give first priority:

- Especially for indigenous and forest-based populations, data sovereignty and consent procedures are crucial.
- Access to digital carbon markets based on equity.
- Algorithms' auditability and transparency mechanisms.

Bassi et al. (2020) underline the need of ethical artificial intelligence frameworks—such as the OECD Principles on AI and the UNESCO Recommendation on AI Ethics—in guaranteeing that smart carbon systems stay fair and inclusive[94].

Furthermore, participatory governance systems—such as community MRV projects and citizen science platforms—can improve the validity and accuracy of carbon monitoring[95]. National policies empowering local governments, NGOs, and academic institutions to engage in carbon governance must back these.

Possibilities for Interdisciplinary Innovation

Smart carbon management's future is at the crossroads of public policy, data engineering, and environmental research[96]. Interdisciplinary research and development ecosystems have to be fostered by means of:

- Innovation centres concentrating on climate technology.
- Collaborations between universities, governments, and businesses.
- Open-source systems for AI-driven environmental solutions.

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In AI-driven climate modelling, satellite IoT convergence, and blockchain-based emissions verification, technological advances are expected[97]. These developments will improve predictive power and lower transaction costs in worldwide carbon markets[98].
Projects like Microsoft's Planetary Computer and Google's AI for the Environment, for example, show how technology firms can support worldwide environmental data control[99]. Such projects, then, have to be in line with public policy objectives and driven by ethical criteria.
Smart carbon management provides a paradigm change in how carbon is tracked, confirmed, and eliminated[100]. But forward-looking regulations and governance systems are absolutely necessary if new technologies are to have worldwide influence. Building scalable and ethical smart carbon ecosystems requires regulatory harmonisation, financial incentives, inclusive governance, and multidisciplinary innovation to converge[101].
Policymakers have to recognise the double function of technology—not just as a tool for efficiency but also as a driver of fairness, transparency, and environmental justice[102]. Smart carbon management can only benefit the earth and its people if digital technologies are integrated into a strong policy framework[103].

6. CONCLUSIONS:

Digital technologies including artificial intelligence (AI), big data, the Internet of Things (IoT), and blockchain are converging to change the scene of carbon management. Smart carbon management systems provide a crucial route for improving the accuracy, openness, and scalability of carbon dioxide removal (CDR) initiatives as countries struggle with the growing consequences of climate change. Realising the full potential of these technologies, however, calls for proactive and inclusive policy interventions that match innovation with environmental justice, regulatory responsibility, and worldwide climate objectives more than merely technological development.
Establishing strong and consistent regulatory systems to enable digital monitoring, verification, and reporting (MRV) of carbon emissions and removals is among the most urgent requirements. Trust in smart carbon systems is still being eroded by fragmented governance, uneven data standard. However, the scene

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of carbon management is undergoing a transformation due to the convergence of digital technologies such as artificial intelligence (AI), big data, the Internet of Things (IoT), and blockchain. Carbon dioxide removal (CDR) and the fight against climate change is a rapidly escalating problem that calls for a crucial route to improving the accuracy, openness, and scalability of any such initiatives, and smart carbon management systems offer just that trail. However, it is only with active and inclusive policy intervention that the full potential of these technologies can be realised; one that matches innovation with environmental justice, regulatory responsibility and with those worldwide climate goals.

Among the most urgent requirements is to establish strong and consistent regulatory systems for allowing digital provision of carbon emissions and removals monitoring, verification, and reporting (MRV). Fragmented governance, versions of data standards that do not align, and not any legally enforceable process are still eroding trust in smart carbon systems. Whenever these instruments are to be widely used especially in international carbon markets, then governments and multilateral organisations have to offer uniform certifications, audit systems and data governance policies. ds, and the absence of legally enforceable procedures. Governments and multilateral organisations have to provide uniform certifications, audit systems, and data governance policies if these instruments are to be widely used—especially in international carbon markets. Regulatory clarity guarantees that digital sensors and AI models used for carbon accounting are consistent, verifiable, and cross-jurisdictional interoperable.

Policy-driven incentives will also be rather important in expanding smart carbon technology. Innovation has to be rewarded not just by research funding but also by means such carbon pricing integration, performance-based tax credits, and subsidies for smart MRV infrastructure. Forward-looking laws like the U.S. Inflation Reduction Act and the EU's Green Deal show how fiscal policy may encourage private sector involvement in carbon technology. Moreover, encouraging public-private collaborations and allowing open-source technology ecosystems can lower implementation costs and support fast scalability, particularly in limited resources environments.

Future policy design ought to be centred on equity and ethics. Smart carbon technologies should neither aggravate current inequities or marginalise at-risk populations. Inclusive policy frameworks should guide the resolution of issues like data sovereignty, consent, and fair benefit sharing. Building trust and guaranteeing social sustainability depend on participatory governance systems—where local communities, indigenous peoples, and grassroots organisations participate in the development, execution, and benefit-sharing of carbon projects.

Furthermore, climate finance organisations have to change to assist the digital transformation of carbon management systems. Reallocating international climate money towards smart MRV technology, particularly in the Global South, will help close the digital gap and guarantee that poor countries are not left behind in the carbon economy. Including smart carbon technologies into Nationally Determined Contributions (NDCs) and national climate policies would help to embed them in long-term mitigation strategy.

Ultimately, the future of carbon management will be determined by the governance systems controlling, funding, and scaling as well as by technology developments as much as by the latter. Though smart carbon management has the ability to transform our tracking and reduction of atmospheric CO_2, this potential can only be realised if it is supported by ethical, inclusive, forward-looking policy frameworks. The foundation of a sustainable and climate-resilient future will be a cooperative worldwide effort combining technology, policy, and equity.

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