Global Journal of Engineering and Technology Advances
eISSN: 2582-5003
Cross Ref DOI: 10.30574/gjeta
Journal homepage: https://gjeta.com/

(REVIEW ARTICLE)

Harnessing big data analytics for environmental protection: Benefits, current applications, challenges and future prospects

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Global Journal of Engineering and Technology Advances, 2025, 24(01), 218-228

Publication history: Received on 19 June 2025; revised on 27 July 2025; accepted on 30 July 2025

Article DOI: https://doi.org/10.30574/gjeta.2025.24.1.0230

Abstract

As environmental challenges grow more complex and interconnected, big data analytics has emerged as a transformative force in advancing sustainable environmental management. By enabling the real-time collection, integration, and analysis of massive, heterogeneous datasets—from satellites, sensors, social media, and citizen science platforms—big data supports enhanced monitoring, predictive modeling, and evidence-based decision-making across a wide range of environmental domains. This article offers a comprehensive overview of the key benefits and practical applications of big data analytics in air quality monitoring, climate change modeling, biodiversity conservation, waste management, and water resource governance. It also examines critical cross-cutting challenges, including data integration, infrastructure disparities, algorithmic transparency, privacy concerns, and evolving legal frameworks. Looking ahead, the article explores emerging frontiers such as artificial intelligence, blockchain, edge computing, and the expanding roles of citizen science and international cooperation. The findings highlight the urgent need for responsible, equitable, and inclusive data-driven approaches to environmental protection and global sustainability.

Keywords: Big Data Analytics; Environmental Protection; Environmental Monitoring; Sustainable Development; Artificial Intelligence; Environmental Policy; Data Governance; Predictive Modeling; Smart Cities; Environmental Sustainability

1. Introduction

The 21st century is marked by an escalating convergence of environmental crises—ranging from climate change and biodiversity loss to deforestation, freshwater scarcity, and pollution. These challenges are complex, interconnected, and accelerating in both frequency and intensity across the globe. Traditional environmental monitoring methods, such as manual field surveys, intermittent sampling, and paper-based reporting, are increasingly insufficient for responding to these issues with the speed and precision they demand [1]. The recent intensification of wildfires, floods, and heatwaves has underscored the urgent need for high-resolution, real-time data to inform timely and effective decision-making [2]

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The COVID-19 pandemic further catalyzed the digital transformation of environmental monitoring systems, highlighting the utility of remote sensing technologies, AI-powered analytics, and decentralized data platforms for maintaining environmental oversight under constrained conditions [3,4]. These developments have paved the way for a paradigm shift toward data-intensive environmental governance.

Big data analytics represents a foundational element of this shift. It enables the real-time collection, integration, and analysis of massive, heterogeneous datasets derived from satellites, drones, Internet of Things (IoT)-enabled sensors, citizen science platforms, and administrative records. These diverse sources allow for the detection of fine-grained spatial and temporal patterns that were previously unobservable. For instance, hyperlocal environmental hazards can now be detected through mobile app submissions and social media reports, complementing remote sensing and weather modeling systems.

In geographic research, this data-rich paradigm has given rise to a “data-driven geography,” where big data’s four defining characteristics—volume, velocity, variety, and veracity—are leveraged to continuously monitor dynamic spatial phenomena [5]. Similarly, in ecological and socio-environmental systems, data fusion techniques support predictive modeling and adaptive management, enabling more responsive and resilient governance.

Governments and international organizations are increasingly institutionalizing big data in environmental management frameworks. The European Commission’s Copernicus Program, for example, offers comprehensive Earth observation data to monitor ecosystems, atmospheric composition, and land-use dynamics—directly informing climate policy and regulatory compliance [6]. Likewise, Kharrazi et al. [1] demonstrate how network-based resilience modeling in China’s Heihe River Basin can inform sustainable water resource planning in complex socio-ecological systems.

This article provides a comprehensive overview of the role of big data analytics in environmental protection. It begins by outlining the key benefits of big data analytics in enhancing monitoring, forecasting, resource optimization, and promoting sustainable practices. It then examines current applications across sectors such as air quality, climate modeling, biodiversity conservation, water resource management, and waste systems. The paper also explores cross-cutting challenges—including data governance, privacy, ethical use, and digital inequity—and concludes with a discussion of emerging opportunities in artificial intelligence (AI), blockchain, edge computing, participatory science, and international cooperation.

2. Benefits of Big Data Analytics in Environmental Protection

Big data analytics offers transformative benefits for environmental protection by enhancing monitoring, forecasting, resource optimization, and promoting sustainable practices. Through the integration of vast and diverse datasets, it enables the identification of trends, the prediction of environmental hazards, and the development of data-informed strategies—ultimately strengthening the effectiveness, equity, and agility of environmental governance.

2.1. Enhanced Environmental Monitoring and Prediction

2.1.1. Real-Time Data Collection

Big data technologies support continuous environmental monitoring by integrating sensor networks, satellite imagery, mobile devices, and social media feeds—surpassing the spatial and temporal limitations of traditional data collection. For example, satellite-derived ammonia maps have revealed emissions from industrial swine operations in marginalized U.S. communities, often missed by ground-based sensors [7].

2.1.2. Predictive Modeling

Machine learning models trained on both historical and real-time data can forecast environmental hazards such as flooding, pollution, or disease outbreaks. Digital trace data has been used to evaluate the disproportionate impact of extreme events—such as Hurricane Harvey—on vulnerable populations, supporting more equitable emergency planning [8].

2.1.3. Climate Change Modeling

Big data strengthens climate change modeling by merging observational data with computational simulations to predict trends in global temperature rise, sea-level change, and the frequency of extreme weather events. These insights inform adaptation and mitigation strategies across national and global policy frameworks [9].

2.1.4. Early Warning Systems

The predictive power of big data analytics also enhances early warning systems. By analyzing inputs from traffic sensors, weather data, and social media, big data has improved emergency preparedness and evacuation strategies. During Hurricane Harvey, such analytics supported rapid response coordination [10].

2.2. Improved Resource Management

Big data analytics plays a pivotal role in improving the efficiency and sustainability of natural resource management across sectors such as water, energy, waste, and biodiversity.

2.2.1. Water Resource Management

Big data platforms, particularly in Southern Africa, have been used to model groundwater levels, detect leaks, and optimize distribution. These systems integrate hydrological, meteorological, and satellite data. For example, Gaffoor et al. [11] highlight the value of multi-source integration in water stress monitoring, while Bata et al. [12] demonstrate that hybrid machine learning models—combining clustering and regression trees—can double the accuracy of short-term urban water demand forecasts compared to traditional models.

2.2.2. Energy Efficiency

By analyzing building-level energy data alongside meteorological variables, big data enables precise load forecasting, dynamic pricing, and renewable energy integration. These capabilities facilitate smart grid operations and emissions reductions, contributing to broader sustainability goals [13].

2.2.3. Waste Management

Predictive analytics using sensor data and temporal waste patterns can optimize collection logistics, reduce operational costs, and minimize environmental impacts. For instance, de Morais et al. [14] introduced a sensor-driven reverse logistics model that dynamically adjusts collection routes using real-time data and machine learning.

2.2.4. Forestry and Biodiversity Conservation

Advanced deep learning models applied to satellite imagery from missions such as Sentinel and Landsat allow high-resolution tracking of deforestation, habitat degradation, and species distributions. These techniques support conservation through near real-time alerts, enforcement against illegal logging, and scientifically informed habitat assessments [15,16].

2.3. Promoting Sustainable Practices

Big data analytics advances sustainable development by optimizing operations across agriculture, urban infrastructure, and global supply chains.

2.3.1. Precision Agriculture

Precision agriculture integrates data from soil sensors, drones, and climate models to optimize irrigation, fertilizer application, and pest control. These data-driven interventions improve yields, reduce water and chemical usage, and limit environmental degradation [17].

2.3.2. Smart Urban Development

Smart city platforms use big data to manage traffic, monitor air quality, and enhance infrastructure efficiency. Climate-smart technologies, such as satellite-based CO_2 emission monitoring, have enabled near real-time assessments across more than 1,500 cities worldwide [18].

2.3.3. Sustainable Supply Chains

In logistics and supply chain management, big data enables dynamic route planning, demand forecasting, and inventory optimization—reducing fuel consumption, improving operational efficiency, and lowering carbon emissions [19].

2.4. Informing Environmental Policy and Governance

Big data supports robust, evidence-based policy development and regulatory enforcement by enabling dynamic risk assessments, community engagement, and real-time policy evaluation.

For example, geographic information systems (GIS) and demographic analysis have been used to identify communities most at risk of flooding and pollution. During Hurricane Harvey, volunteered geographic information (VGI)—including tweets and crowd-sourced imagery—augmented official satellite data, guiding emergency response [20].

Regulatory agencies are increasingly integrating continuous data streams into iterative policy processes. The U.S. Environmental Protection Agency's EJScreen platform merges pollution and demographic data to support environmental justice initiatives [21]. Community-based efforts, such as CleanAirNowKC, empower residents to deploy air quality sensors and co-produce environmental data. These efforts strengthen transparency and enhance the legitimacy of environmental governance [22].

3. Current Applications of Big Data Analytics in Environmental Protection

Big data analytics has transitioned from a theoretical framework to a practical toolset for advancing environmental protection. By integrating structured and unstructured data—from satellite imagery and ground-based sensors to climate models, mobile devices, and social media—big data enables high-resolution, real-time monitoring and management of ecological systems. These capabilities enhance environmental modeling, forecasting, and decision-making at multiple scales, from localized interventions to global sustainability frameworks.

The proliferation of open-access environmental datasets (e.g., Copernicus, Landsat, MODIS, NOAA) and the advent of scalable cloud computing platforms (e.g., Google Earth Engine, NASA Earth Exchange) have accelerated the deployment of machine learning and geospatial analytics. Governments, research institutions, NGOs, and private-sector actors increasingly leverage these technologies to monitor ecosystems, enforce regulations, and plan for long-term sustainability.

The sections below highlight key domains in which big data analytics is being effectively deployed, emphasizing real-world applications and evidence-based outcomes.

3.1. Monitoring and Managing Air Quality

Big data analytics significantly improves the spatial and temporal resolution of air pollution monitoring through the fusion of IoT sensor networks, satellite imagery, and mobile-based data streams. Advanced algorithms detect pollution hotspots, forecast air quality index variations, and inform targeted mitigation strategies.

For example, researchers in California equipped Google Street View vehicles with air quality sensors, generating hyper-localized pollution maps in cities like Oakland. This initiative revealed stark disparities in pollution exposure across neighborhoods [23]. Similarly, in China, smart city systems have deployed low-cost sensors integrated with cloud platforms to monitor urban air quality in real-time, supporting policy and health interventions [24].

3.2. Climate Change Prediction and Scenario Modeling

Big data underpins climate change modeling by aggregating long-term datasets on meteorology, land use, oceanic temperatures, and atmospheric composition. These datasets feed into global circulation models (GCMs) and downscaled regional models to simulate future climate scenarios.

NASA's Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) leverage high-performance computing and downscaling techniques to model global warming impacts under different Representative Concentration Pathways [25]. In the Netherlands, the Deltares institute integrates big data into sophisticated hydrological modeling tools—such as Delft-FEWS, Delft3D FM, and the Delft-FIAT flood impact assessment system—to forecast flood risks and support infrastructure resilience planning under sea-level rise and climate uncertainty [26].

3.3. Biodiversity and Wildlife Conservation

Big data analytics supports biodiversity conservation through enhanced species monitoring, habitat mapping, and illegal activity detection. Data sources include camera traps, acoustic monitoring, drone imagery, satellite data, and citizen science platforms.

The Global Biodiversity Information Facility aggregates species occurrence data from institutions worldwide, aiding in conservation planning and ecological research. Automated species recognition, driven by machine learning models trained on camera trap images—such as those developed under Microsoft's AI for Earth initiative—reduces manual labor and error in species classification [27]. Additionally, platforms like Global Forest Watch use satellite-derived alerts to monitor deforestation in near real time, facilitating timely enforcement actions [28].

3.4. Waste Management and Pollution Control

Big data is central to optimizing waste management systems and detecting pollution through real-time monitoring and predictive analytics.

3.4.1. Optimized Collection with Integrating Radio Frequency Identification (RFID) and IoT

Municipalities worldwide have adopted RFID-enabled bins and GPS-tracked collection vehicles to streamline waste operations. These systems optimize route planning and reduce fuel consumption and emissions [29].

3.4.2. Predictive Analytics and Landfill Forecasting

Machine learning models predict future waste volumes, enabling proactive planning and landfill management. AI-based forecasting tools can achieve over 85% accuracy and help extend landfill lifespan while minimizing environmental impact [30].

3.4.3. AI-Driven Detection of Illegal Dumping

In North Geelong, Australia, a semi-autonomous system leveraging CCTV footage and AI was deployed to identify illegal dumping. The system resulted in 26 infringement notices totaling AUD 20,000 and saved over 180 hours annually in manual surveillance [31].

3.4.4. Real-Time Pollution Forensics

Across Europe, wastewater treatment facilities use real-time sensors and data analytics dashboards to detect contaminants—such as microplastics or chemical residues—enabling immediate response and improved water quality management [32].

3.5. Water Resource Management

Big data tools are increasingly employed in water management to monitor availability, forecast scarcity, and manage consumption. These systems integrate data from satellite remote sensing, weather models, hydrological sensors, and user-reported inputs.

In India, the India-WRIS platform combines meteorological, hydrological, and satellite data to monitor water resources and predict monsoon behaviors, supporting agricultural planning and drought preparedness [33]. In sub-Saharan Africa, mobile phone-based systems allow communities to report water shortages, which are analyzed via big data analytics to optimize water distribution and emergency response strategies [34].

3.6. Environmental Policy and Governance

Big data supports improved environmental governance by enhancing transparency, automating assessments, and enabling participatory monitoring. Automated Environmental Impact Assessments uses satellite data and AI algorithms to pre-screen development sites for environmental risk. Drone and Satellite Surveillance was used for compliance monitoring in deforestation zones, mining regions, and protected ecosystems [35]. Crowdsourced reporting platforms that integrate social media and mobile apps allow citizens to report incidents of pollution, wildlife trafficking, and illegal logging. These citizen reports are increasingly verified and enriched with geospatial data to support enforcement and community monitoring [36]. The European Union's Copernicus Program exemplifies large-scale environmental data governance. It utilizes data from a constellation of Sentinel satellites to monitor land, marine, and atmospheric conditions across the EU. The resulting datasets are integrated into decision-support systems that inform EU climate policy, agricultural planning, biodiversity conservation, and disaster response [37].

4. Challenges of Big Data Analytics in Environmental Protection

While big data analytics offers powerful tools for tackling complex environmental problems, its implementation presents a range of challenges across technical, infrastructural, legal, and ethical domains. Overcoming these barriers is essential to ensuring the responsible, equitable, and effective deployment of data-driven environmental solutions.

4.1. Data Integration and Standardization

Environmental big data is inherently heterogeneous, originating from diverse sources such as satellite imagery, ground-based IoT sensors, governmental databases, and even social media platforms. These datasets often vary in format, spatial resolution, temporal granularity, and metadata conventions, complicating their integration and harmonization.

For example, aligning satellite-derived land use classifications with real-time weather station data requires advanced preprocessing steps, including spatial re-projection, temporal synchronization, and standardization of measurement units. Such technical complexity is further compounded by the absence of universally accepted metadata standards and data-sharing protocols, which hinders interoperability across systems, limits replicability, and impedes cross-sectoral collaboration.

Addressing these integration challenges necessitates investment in interoperable data infrastructures, the development of standardized ontologies, and the adoption of rigorous data governance frameworks [38,39].

4.2. Infrastructure and Capacity Gaps

Significant disparities exist in the technological infrastructure and human capital required to implement big data solutions, particularly between high-income and low-income regions. Many developing countries lack access to high-speed internet, data storage capabilities, reliable power supply, and trained personnel, thereby limiting their ability to generate, process, and act on environmental intelligence.

This digital divide not only inhibits localized environmental monitoring but also exacerbates global inequities in environmental resilience and adaptive capacity. Bridging this gap requires strategic investments in cloud computing, regional data centers, open-source tools, and long-term capacity-building initiatives. Public-private partnerships and international development agencies play a key role in extending these capabilities to underserved communities [3].

4.3. Model Interpretability and Decision Support

As machine learning and artificial intelligence become increasingly central to environmental data analysis, concerns about the interpretability of these models have gained prominence. While advanced algorithms can yield accurate forecasts and classifications, their inner workings often remain opaque—posing challenges for policy transparency and accountability.

Black-box models, in particular, may not offer clear rationales for their predictions, undermining stakeholder confidence and limiting their utility in regulatory or legal contexts. To bridge this gap, there is a growing emphasis on explainable AI, which seeks to make model outputs more transparent and intelligible to non-technical users, such as environmental managers and policymakers. Incorporating human-in-the-loop approaches can also enhance interpretability and foster trust in AI-driven systems [40].

4.4. Governance and Legal Challenges

The governance of environmental big data remains underdeveloped in many jurisdictions. Legal ambiguities often arise in the context of transboundary data flows, satellite surveillance, and cross-sectoral data sharing. Questions surrounding data ownership, intellectual property rights, liability for data misuse, and jurisdiction over environmental harm are frequently unresolved in existing legal frameworks.

Establishing coherent and harmonized regulatory structures—both nationally and internationally—is essential to clarify responsibilities, promote transparency, and foster cross-border cooperation in environmental data governance. Such frameworks must balance innovation with accountability while addressing emerging ethical and legal complexities [6].

4.5. Data Privacy and Ethical Use

Big data applications in environmental protection increasingly involve human-centered data, including geolocation, mobility patterns, and behavioral indicators derived from mobile devices and social platforms. This raises substantial concerns about individual privacy, consent, and the potential for surveillance.

For instance, air pollution studies that leverage smartphone-based sensors or vehicle GPS data may inadvertently expose sensitive information about individuals or communities. To mitigate these risks, ethical data governance is paramount. Best practices include securing informed consent, anonymizing datasets, limiting access through secure protocols, and ensuring that data use aligns with societal values and public interest [41,42].

5. Future Prospects

As environmental challenges grow in scale and complexity, the urgency for transformative, technology-enabled solutions is becoming more pronounced. While big data analytics has already shown remarkable utility in environmental monitoring, forecasting, and decision-making, its full potential lies in its convergence with emerging digital technologies.

The next frontier in environmental protection will be defined by the integration of artificial intelligence, machine learning, blockchain, edge computing, and participatory platforms such as citizen science—united through globally coordinated data ecosystems. These tools will not only augment the precision, speed, and granularity of environmental intelligence but also enable greater transparency, decentralized data control, and inclusive stakeholder engagement.

Furthermore, the rising frequency of climate-related disasters, ecological degradation, and pollution crises will necessitate adaptive systems capable of delivering real-time interventions. Future environmental governance must therefore transcend static monitoring, embracing dynamic risk prediction, responsive policy mechanisms, and resilient systems planning. Central to these innovations will be international cooperation, equitable access to data infrastructure, and sustained investment in digital capacity building—particularly in underserved and climate-vulnerable regions.

The subsections below outline five key technological domains poised to redefine big data's role in environmental protection.

5.1. Artificial Intelligence, Machine Learning, and Deep Learning

AI-driven analytics are increasingly central to environmental prediction and emergency preparedness. Advanced machine learning algorithms can process multimodal datasets (e.g., satellite imagery, sensor outputs, and meteorological data) to detect anomalies, classify land use, and predict ecosystem responses to stressors.

For example, AI-enhanced systems in Australia have demonstrated success in detecting early-stage wildfires and forecasting extreme weather events such as typhoons, enabling authorities to initiate timely evacuation and mitigation efforts [43,44]. Deep learning approaches—such as Fully Convolutional Data Descriptors—have achieved over 95% accuracy in identifying disaster-affected zones, generating explainable visual heat maps for first responders [45].

5.2. Blockchain for Transparency and Environmental Compliance

Blockchain technology holds promise for enhancing transparency, traceability, and accountability in environmental governance. Its decentralized, tamper-proof architecture is especially suited for carbon credit tracking, supply chain monitoring, and environmental disclosure.

Recent innovations include blockchain-enabled maritime monitoring systems that integrate IoT sensors with smart contracts to ensure compliance with MARPOL environmental regulations in real-time [46]. Blockchain-based ESG reporting tools are also being deployed to combat greenwashing, enabling immutable verification of sustainability claims across sectors [47]. The Open Forest Protocol is one such initiative leveraging blockchain to validate forest carbon offsets and biodiversity conservation outcomes [48]

5.3. Edge Computing and IoT

Edge computing, which enables local data processing on or near data sources, is increasingly vital for time-sensitive and bandwidth-constrained environmental applications. Unlike traditional cloud architectures, edge systems offer reduced latency, improved reliability, and lower energy consumption.

These benefits are particularly valuable for environmental monitoring in remote regions, such as real-time fire detection in forests, early flood warnings in mountainous areas, and autonomous wildlife surveillance [49]. By bringing analytics closer to the edge, environmental agencies can respond faster to ecological changes while minimizing data transmission costs and infrastructure bottlenecks.

5.4. Citizen Science and Crowdsourced Environmental Monitoring

Citizen-generated data is becoming an essential complement to traditional monitoring networks. Mobile apps, participatory platforms, and open-source tools enable the public to contribute to biodiversity inventories, pollution tracking, and land-use change observations.

For instance, platforms like *Chronolog* allow park visitors to submit repeat photos of landscapes, which are then used to track seasonal and anthropogenic changes over time [50]. Similarly, mobile tools empower users to report wildlife sightings or illegal activities, which are then verified via GPS-tagged data and cross-validated with official datasets. These efforts democratize environmental science, improve spatiotemporal data granularity, and promote community stewardship [51].

5.5. International Collaboration and Capacity Building

Global environmental protection requires interoperable data systems and cross-border collaboration. Initiatives such as the Group on Earth Observations (GEO) and the United Nations Environment Program's World Environment Situation Room foster standardized data collection, sharing, and analytics to support coordinated action [52].

Capacity building—through open data access, digital literacy programs, and cloud infrastructure support—is critical to ensure that developing nations and marginalized communities can fully participate in and benefit from big data-driven environmental governance.

6. Conclusion

The advancement and integration of big data analytics have ushered in a paradigm shift in environmental protection, offering transformative tools to enhance the precision, scope, and agility of environmental monitoring, assessment, and policy-making. By aggregating and analyzing diverse data streams—from satellite imagery and IoT sensors to mobile applications and administrative databases—big data enables a more dynamic and granular understanding of complex ecological systems.

This capability has demonstrated value across key environmental domains, including air quality regulation, climate modeling, biodiversity preservation, and waste management. Techniques such as machine learning, geospatial analysis, and predictive modeling have significantly improved early warning systems, resource optimization, and adaptive governance strategies. These applications are especially vital in an era characterized by accelerating environmental degradation and interlinked global challenges.

However, the deployment of big data technologies is not without its constraints. Critical issues such as data standardization, governance, privacy, algorithmic bias, and digital inequality remain pressing. The lack of universal data-sharing protocols and equitable access to analytical infrastructure further exacerbates disparities, particularly in under-resourced regions. Addressing these challenges requires comprehensive regulatory frameworks, ethical guidelines, and collaborative international partnerships.

Looking ahead, the convergence of big data with emerging technologies—such as artificial intelligence, edge computing, blockchain, and participatory Citizen science platforms—holds promise for expanding the reach and impact of data-driven environmental strategies. These innovations can enhance data transparency, support real-time interventions, and promote inclusive decision-making across multiple governance levels.

In sum, while big data analytics is not a standalone solution to global environmental crises, it represents a foundational enabler of evidence-based, responsive, and equitable environmental governance. Realizing its full potential will depend not only on technological innovation but also on ethical stewardship, institutional cooperation, and sustained global investment in capacity building and digital inclusivity.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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