

Predictive Environmental Governance: Role of IoT and Artificial Intelligence in Environmental Monitoring in the Niger Delta

Ukadike Ifeanyi Destiny; Okwonu Friday Zinzendoff; Akazue Maureen I.

¹University of Delta, Agbor.

²Department of Mathematics, Delta State University, Abraka.

³Department of Information Systems Management, Delta State University, Abraka

Publication Date: 2026/09/16

Abstract: Nigerian environmental governance, particularly in the Niger Delta region, has been characterized by reactivity as an approach which is very stubborn as if using manual inspection, lengthy laboratory processes, and report generation, none of which are aligned to the dynamics of pollution generation. This research presents an analysis and synthesis of literature that has been published between 2020 and 2025 about the interplay of IoT, artificial intelligence (AI), machine learning (ML), and cloud-based analytics in advancing the development and deployment of predictive environmental management in response to the existing reactive model. By utilizing well over sixty scholarly sources that have been conducted primarily for the air, water, and soil monitoring in both developed and developing countries, the paper traces the evolution of the process of environmental monitoring from manual processes and early-stage sensor solutions to predictive designs while considering various machine learning models, sensor networks, and decision-making procedures. The results generated by those technologies include early warning, compliance monitoring, enhanced community protection, and improved accountability, despite the complexities associated with implementation. Nevertheless, the paper also mentions a number of impediments that hinder the use of predictive environmental governance in resource-constrained and oil-producing settings such as gaps in infrastructure, problems of data governance, cybersecurity threats, and institutional readiness challenges. Lastly, the paper provides recommendations for implementing a transition to predictive environmental governance in Nigeria in phases.

Keywords: Predictive Environmental Governance, Internet of Things, Artificial Intelligence, Machine Learning, Niger Delta, Environmental Monitoring.

How to Cite: Ukadike Ifeanyi Destiny; Okwonu Friday Zinzendoff; Akazue Maureen I. (2026) Predictive Environmental Governance: Role of IoT and Artificial Intelligence in Environmental Monitoring in the Niger Delta. *International Journal of Innovative Science and Research Technology*, 11(8), 3657-3666. <https://doi.org/10.38124/ijisrt/26aug1208>

I. INTRODUCTION

One may describe environmental governance as a kind of spectrum, which starts from reactive management, which is about responding to pollution incidents after damage has already been done to the environment and proceeds towards predictive management that involves continuous environmental sensing and prediction so that action could be taken proactively. In the case of Nigeria, for at least several decades since the country's independence, its environmental regulation has been quite clearly situated on the reactive end of this spectrum. In particular, the monitoring has been mostly performed via periodic inspections, laboratory testing of samples and post-incident reporting. Such approach has brought about severe

problems for the monitoring of the environmental situation in oil-producing regions since, for example, spills, gas flaring and pipeline leaks could spread through water bodies and into the farmlands long before any human inspection team would arrive at the spot of the incident.

In the case of the Niger Delta, however, it is especially pronounced. This area with large hydrocarbon deposits, which has powered the economy of Nigeria for over sixty years, has also degraded local ecosystem, fisheries, farmlands and communities due to cumulative environmental damage (Amah et al., 2024). According to the latest assessments, thousands of polluted sites are found across the delta, reflecting the legacy of several decades of oil spillage, crude refining, gas flaring and

inefficient remediating efforts (Amah et al., 2024). While in one sense, the persistence of these environmental problems despite years of regulations could reflect a "lack of policy" approach, in another sense, it reflects structural problems with the monitoring itself and its informational feedback loop.

Globally, however, the monitoring kit has undergone quite an evolution during the past decade or two. Specifically, the convergence of inexpensive embedded sensing technologies, wireless ubiquity, cloud computing, and ever-evolving machine learning technologies led some scholars to speak about "Sensor Environmental Intelligence," or the model of environmental systems predicting the near future in addition to describing the present (Ramani & Sujitha, 2025; Popescu et al., 2024). Such being the case, the question posed in this article is by no means arbitrary but still quite crucial. Namely, what exactly does the existing empirical evidence of feasibility, performance, and governance consequences of IoT- and AI-enabled environmental monitoring say about the feasibility and effectiveness of such a predictive approach, and what would be required for translating this evidence into a functional governance framework suitable for application in the Niger Delta? In this process, this paper aims not at compiling an inventory of environmental technologies but presenting a more specific, evidence-based approach to the necessary institutional transition—from reactive to predictive environmental governance based on empirical performance reported in dozens of recently conducted studies using different methods but converging in the idea of the same governance transition.

➤ *Environmental Degradation in the Niger Delta*

Environmental degradation in the Niger Delta originates from the complex interplay of oil spills, gas flaring, pipeline leakages, industrial discharge and illegal oil refining, each of them contributing to a somewhat different but related web of ecological damage (Amah et al., 2024). Oil spills render soil and ground water unusable for farmland for years ahead; gas flaring constantly pollutes air around communities, which frequently happen to live close enough to flaring zones; and finally, the combined effect of industrial and domestic waste disposal contributes to corrosion of the entire network of creeks and estuaries in the region. As the end result, there is a serious decrease in agricultural productivity, fisheries production, biodiversity, and even the state of public health in the region. However, what makes the Niger Delta stand out among other contaminated regions in the world is the cumulative and, at times, hardly noticeable character of the pollution affecting large and logistically challenging territory of creeks, swamps, and rural communities.

Moreover, any "engineering for detection" here had already been carried out by the time of the latest wave of predictive analytics via AI-based monitoring. For instance, Akpoyibo et al. (2022) designed an oil-spill monitoring surface water robotic system (SWROSS) that was specifically intended for creek-rich landscapes of the Niger Delta, thus, proving the

feasibility of fitting sensor devices in situ prior to the issues of predictive analytics being raised at all.

➤ *Limitations of Traditional Monitoring Systems*

The existing environmental monitoring system of the Niger Delta region, as well as other regions of Nigeria, relies heavily on manual control, periodic laboratory testing, and delayed reports. The following limitations are already known about the said methods of collecting environmental data: they are costly and manpower-consuming; provide an insight into the state of environment at the moment of sample collection, rather than monitor it continuously; poorly deal with remote or inaccessible terrain; and provide "results" once real environmental damage has been done. Ukadike et al. (2023), Ukadike et al. (2024), and Onyagu et al. (2024) have independently proved that in the context of Nigeria, even when there are cheaper IoT alternatives available, they still cannot compete in terms of predictive capabilities of a system with the ones suggested by the international literature. The same conclusion was reached by Okafor et al. (2023) in the domain of solid waste management, where, despite the introduction of ICT as a working tool, its use remained mostly descriptive and recording.

Thus, the gap between the suggestions of international literature and what was operationalized in the Niger Delta is what drives the current empirical synthesis.

II. METHODOLOGY

In turn, an empirical literature analysis methodology is employed here. The data, methodologies, approaches, and numeric results found in the peer-reviewed literature on IoT- and AI-enabled environmental monitoring (2020-2025) are singled out, analyzed and synthesized. In contrast to the traditional narrative literature review, in the analysis process, each of the considered articles is seen as empirical evidence points providing, whenever possible, the particular technical architecture, the specific environmental area in focus (air, water, soil, or waste) and numerical measures of the respective monitoring and pollution mitigation performance achieved, including but not limited to accuracy, error rates, pollution cuts and reduction of the response time. Totally, 63 studies matching the chosen criteria were selected from the wider literature pool underlying the parent research on IoT-based predictive environmental monitoring in the Niger Delta conducted by the author. The studies had to contain information on the IoT-, AI-, or ML-enabled environmental monitoring or pollution-mitigation system along with at least one quantifiable performance indicator.

Thus, through this type of empirical synthesis, the article tries to go beyond the rather common call for "smart" environmental solutions and provides a more specific evidence-based idea of what can be accomplished with the help of predictive environmental governance and in what conditions.

The extraction procedure involved three separate stages. First of all, each of the papers was categorized according to the environmental domain addressed (air quality, water quality, soil contamination, or multi-domain) and the technological approach applied. Thus, the latter could be classic machine learning approach such as Random Forest and Gradient Boosting or various deep learning frameworks (LSTM, CNN-LSTM combinations, and Graph LSTM). Alternatively, the studies using descriptive IoT systems (non-predictive) could be included as comparison points.

Next, in the second stage, the quantitative performance measures specified in each paper, including but not limited to accuracy, R-squared, RMSE, percentage cut in pollution, changes in response time or resource consumption, were collected in tables for cross-paper comparison regardless of the environmental domain and geographic area differences between the papers,

Thirdly, the outcomes related to governance issues such as those connected to compliance to regulation, community health outcomes or institutional decision-making process were isolated. Then, these outcomes were sorted into thematic categories to be able to contribute to the discussion on governance-related benefits elaborated in Section 6. Overall, this multi-step extraction and subsequent thematic summarization which, from some angle, resembles automated data-mining driven context summarization techniques proposed by Atonuje and Egwali (2023) is the part that transforms the present article into something other than a conventional narrative literature review: in essence, all major claims formulated further on are backed up by an explicit empirical outcome, which, in turn, is quantified within the underlying dataset and not just an impression of the field as a whole.

III. THE EVOLUTION OF ENVIRONMENTAL MONITORING

➤ *Traditional Monitoring Methods*

Traditionally, environmental monitoring relied on manual inspections, periodic measurements in situ and laboratory analysis of obtained samples. These methods are, at the point of sampling, quite methodologically rigorous, however, they remain retroactive in nature as the results would come to light days or weeks after sample collection. Thus, at times, short-term pollution spikes might disappear while others can inflict irreparable harm already before any results become known. Furthermore, the spatial reach is also rather limited due to the cost and logistic constraints imposed by the need for manual sampling and is especially pronounced in the stream-rich, inaccessible Niger Delta (Ullo & Sinha, 2020).

➤ *Emergence of Smart Environmental Systems*

However, as a result of the advent of low-cost microcontrollers such as Arduino, ESP32, Raspberry Pi, NodeMCU as well as sensors that have become increasingly

cheaper, deployment of environmental sensing systems through automation has greatly become less burdensome (Okafor et al., 2024). In Nigeria, some examples in this case include the work of Ukadike et al. (2023) where IoT air quality monitoring was realized using the combination of microcontrollers, gas and humidity sensors, and Blynk IoT platform for near real time data visualization and alerts, as well as work of Onyagu et al. (2024) where an IoT enabled environmental sensing network was established using ultrasonic sensor and MQ135 gas sensors to monitor waste-bin fill level as well as air quality around dump sites. Outside Nigeria, Bellini et al. (2022) and Syed et al. (2021) give the spread of environmental, transportation, waste management, and energy IoT enabled sensing in the modern "smart city" environment where the early efforts in IoT enabled environmental sensing in Nigeria fall into the broader context of an emerging global movement.

Indeed, the broader smart city movement is captured in the review paper by Ihama et al. (2025) where smart city development and Internet of Things are discussed. Furthermore, it is complemented by an architecture framework by Ihama et al. (2023). In both approaches, environmental sensing is treated as one of the aspects of an integrated IoT enabled smart city environment rather than a standalone application. Similarly, the same environmental sensing rationale is slowly extending itself to other domestic activities as seen in the work by Akazue, Pirah et al. (2024) where enhanced agriculture greenhouse systems for developing countries were demonstrated.

The maturity of this smart-systems line is visible too in communication design getting more sophisticated. Earlier deployments often used straightforward Wi-Fi or GSM between each sensor node and a single cloud dashboard, but newer structures more often add layered edge-fog-cloud patterns, where early-stage data filtering and anomaly detection happen locally on the sensor node, before the information is pushed upward for later trend analysis in a more centralised cloud setup (Manduva, 2020; Asghar et al., 2025). This change matters a lot for resource-limited areas like the Niger Delta, because edge pre-processing can reduce both bandwidth needs and the power required to keep continuous monitoring going, which is a big deal in regions with unreliable grid electricity and uneven cellular coverage. Going further, Okumoku-Evrero et al. (2025) study how 6G might be integrated and what it could change for IoT devices, implying that upcoming mobile connectivity could meaningfully ease bandwidth and latency constraints that currently limit continuous, high-density environmental sensing in distant riverine landscapes.

IV. PREDICTIVE ENVIRONMENTAL MONITORING

➤ *Conceptual Foundations*

Predictive environmental monitoring kind of extends what "smart sensing" tries to do, because it adds machine learning plus statistical forecasting models that look at both past records and current streams of measurements, kind of to guess what the

environment will be doing later. So, it is not just “here is what we see right now”, it leans toward, “what is likely to happen next, and what should be done before it actually shows up”. In fact, this feels like a pretty basic philosophical shift in how environmental governance gets framed: you stop centering everything on “what is happening now?” and start centering decisions around likely next states. Ramani and Sujitha (2025) lay out this idea pretty clearly as a move from retrospective monitoring to a denser, decision-focused “environmental intelligence,” supported by multimodal data harmonisation and spatio-temporal predictive systems. They also report that in field trials the early-warning lead time can stretch by up to 2.7 days.

Such a shift is more than mere rhetoric as it can be seen in the PRISMA-structured systematic review of over 200 articles in ten environmental domains provided by Polymeni et al. (2022), there is a visible internal evolution of predictive techniques in the literature under consideration. From simple regression modeling in the first studies to artificial neural networks in the mainstream and, then, to more specialized recurrent and hybrid networks designed to accommodate temporal and spatial dependencies typical of environmental data sets, the evidence base indicates that environmental prediction does not seem to remain some static tool once acquired. Rather, it appears to be an evolving methodology boundary with quite tangible changes in the notion of “state of the art” even within a five-year review period.

➤ *Data-Driven Environmental Management*

Data-driven environmental management relies on a constant supply of high-quality data from several sources and conversion of such information into actionable predictions through predictive models. As it is mentioned in Popescu et al. (2024), the success of the whole endeavor depends greatly on balancing model accuracy with constraints in sharing and computational complexity of the process, especially in limited resources setting. Rahaman (2025), analyzing several locations in Beijing, Rotterdam, and Ganges River basin, also reports that a combination of IoT, AI, and, in some cases, blockchain technology produces the high-resolution environmental pollution data suitable for regulatory actions that cannot be delivered in such efficient manner by traditional, lab-based monitoring methods.

Among the recurring topics in data-driven management literature is a quality of collected data and reliability of used sensors since no prediction can occur without quality data and reliable sensors. Okafor et al. (2024) specifically emphasize that downstream machine learning predictions can be only as good as sensor inputs; besides, environmental IoT networks in harsh conditions, such as humid, saline and flood-prone areas like Niger Delta, have to deal with sensor drift, biofouling, and calibration deterioration. This matches the findings of Polymeni et al. (2022) on sensor stability as one of the knowledge gaps not widely explored in this broader context. Thus, this particular aspect implies that the proposed monitoring model would have

to be designed with automatic recalibrations, redundancies and ground truth validations based on laboratory standards incorporated within it.

V. **IoT AND AI AS GOVERNANCE TOOLS**

➤ *Sensor Networks*

Physical sensors that capture such variables as particulate matter, toxic gas content, water turbidity, chlorine concentration, temperature and humidity represent the heart of any predictive environmental monitoring system. Asha et al. (2022) provide an example of distributed IoT sensor arrays capable of detecting eight different pollutants, such as NH₃, CO, NO₂, CH₄, CO₂ and PM_{2.5}, and transmitting the information via cloud gateways to achieve fast processing of the data. Also, Chinnappan et al. (2023) outline a portable low-infrastructure sensor node that can measure chlorine concentration in remote waters and state an R-squared of 0.94 between predictions and the lab-measured values. This means that sensor networks can reach laboratory-grade precision while being constantly active and operational in remote locations. From the point of view of governance, the potential benefit is evident because in case of Niger Delta, the laboratory facilities are usually located in just a few urban centers only.

As an example of how a sensor node designed for remote location deployment may look, Akpoyibo et al. (2022) floating SWROSS platform, which was specifically designed to detect oil spills on the surface of the water, can be considered.

The second, equally significant aspect of designing a sensor network is its durability and portability to address the reality of the field operation environment. This aspect is clearly stressed by Chinnappan et al. (2023), who speak of the “portability” of their chlorine-monitoring node that was designed to be placed in remote water zones without any infrastructure support, and indeed this is quite relevant to the operation conditions in the Niger Delta, where fixed installations face flooding, vandalism, and theft, with most suitable locations accessible by boat only. Therefore, the sensor network architecture that would suit this environment should not only focus on prediction accuracy but also consider physical resilience, minimizing any required maintenance, as well as aiming at energy independence, through solar power generation or some other form of ambient energy harvesting, which is the theme common for the broader discourse of “Green IoT” (Almalki et al., 2023).

Obire et al. (2026) offer one particular way of incorporating resilience and security into the design of such field sensors. The authors discuss an IoT-based smart distribution metered system that includes real-time occupancy sensing and inbuilt security encryption standards. The underlying design principles, like continuous sensing in conjunction with tamper-proof security measures in the sensor node, are fairly easily transferable to the case of environmental

sensor nodes used in exposed, sparsely monitored environment like the Niger Delta.

➤ *Machine Learning Models*

Once environmental data is collected, machine learning models become active, providing predictions and classifications. Empirical literature presents rather a wide range of modeling techniques, each suitable for a particular application case. For instance, in terms of air quality forecasting, Almalawi et al. (2022) use a stacked ensemble learner that uses Random Forest, XGBoost, and Multi-Layer Perceptron and achieves 94.8% of predictive accuracy. In turn, Alqahtani and Kshirsagar (2024) have found Gradient Boosting-based models to reach 95.1% accuracy in detection of water pollution and 92.4% accuracy in air quality prediction in the unified multi-domain AI-IoT environment. In the field of time series forecasting, Polymeni et al. (2022), who conducted a PRISMA-based survey analysis of over 200 papers, noticed a tendency towards shifting from “plain” Artificial Neural Networks towards Long Short-Term Memory (LSTM) networks and their hybrids with CNN, since the latter is capable of modeling temporal dependencies in environmental time-series better. Ramadan et al. (2024) have also proposed a Hybrid Deep Learning approach which uses Gated Recurrent Units and spatial attention and allows reaching RMSE of 0.042 when predicting up to twelve hours into the future the industrial pollutant plume dispersion.

Still, classical non-deep-learning approaches are able to maintain their competitiveness in some aspects of the Nigerian ICT field. Thus, Ihama et al. (2025) have used a supervised Support Vector Machine algorithm to predict vehicular movements. The given methodology example illustrates how “lighter” traditional machine learning algorithms are able to provide reliable predictions for a short period of time, which is quite relevant in case when a new environmental monitoring region gets instrumented and possesses not much data, e.g., in Niger Delta. As for compute-intensive approaches, Azanor et al. (2025) have described the enhanced deep learning algorithm for real-time vital signs monitoring. The given application is related to the health domain but its structural framework of continuous stream forecasting is rather similar to the one required by continuous environmental sensor-stream prediction.

Altogether, those results show that modern machine learning models are able to reach accuracy levels in the low-to-mid nineties in different environmental areas. That performance is not only “nice” in experimental aspect, it is the one which is able to support deployment rather than proof-of-concept experiments.

It does not seem like there is any single model architecture which would appear to be best in every situation, on the contrary, it seems that the choice of a certain model really

depends on the environmental domain, on the amount of available training data and on the computational resources available at the time of deployment. The benefits of ensemble learning techniques employed by Almalawi et al. (2022), on the contrary, become apparent precisely in the case of rather limited training datasets – averaging over several base learners lowers the risk of overfitting to a relatively small historical sample, which is rather an expected problem in the case of a newly instrumented territory such as Niger Delta. LSTM and other similar types of deep learning approaches, on the contrary, tend to demonstrate their strengths precisely as the volume of available historical data grows, therefore, it might be reasonable to start the adoption of AI tools for Niger Delta with some ensemble approaches or even traditional approaches as described by Ihama et al. (2025), and proceed with deeper models in the future, gradually following the general path of model evolution outlined by Polymeni et al. (2022).

➤ *Real-Time Decision Support*

Apart from predictive functionality, the reviewed systems also offer an additional decision support layer, which converts predictions into recommendations or, possibly, automatic actions. In particular, Baranwal (2025) describes the concept of Smart Traffic-Pollution Linkage model that features a reinforcement-learning agent making recommendations on traffic diversions in the event of reaching nitrogen dioxide levels that are getting close to being dangerous and mentions 15-20% reduction in local peak pollution. Furthermore, Hoang et al. (2022) also point out the importance of transition from the “passive” sensing to “active” acting, where AI Real-Time Control algorithms are able to control industrial filtration and chemical dosing systems automatically just to ensure that the emission stays within legal limitations. The general concept of software agents acting autonomously for the operator once certain decision-making criteria are satisfied is not actually new within the realm of information technology in general: for instance, Okumoku-Evoro et al. (2017) already mentioned software agents in e-commerce applications and explained how autonomous agents could monitor certain criteria and perform operations independent of direct human involvement. This kind of approach can be considered a commercial version of the same agent-based automation used today in environmental control applications. In the context of Niger Delta, where in the past it took weeks or days to take action after the environmental detection, ability of these technologies to reduce this timeframe to a matter of minutes or hours can be the most crucial governance outcome of these technologies.

VI. BENEFITS OF PREDICTIVE GOVERNANCE

➤ *Early Warning Systems*

Increased early warning lead time is the most often mentioned advantage in the reviewed studies. Thus, Ramani and Sujitha (2025) point to a 2.7-day increase in the lead time of early warnings in desertification risk cases; Narayana et al. (2024) highlight that their Internet of Things (IoT)-based Environmental Monitoring System allows detecting the

environmental degradation triggers up to 48 hours prior to the exceeding of the crucial threshold; and Asghar et al. (2025) observe a 40% decrease in the system latency during simulation of emergency situations through hybrid edge-cloud computing. In the context of the Niger Delta with its oil spills and gas leaks spreading across water basins within hours, increased early warning lead time can have tangible implications on minimizing ecological harm and human exposures.

It is essential to acknowledge the versatility of lead-time improvement observed in the context of diverse environmental issues ranging from desertification and soil deterioration to industrial gas releases and urban air quality crises. That makes one conclude about the general nature of the predictive capacity of the technology at hand, which is the reason behind the convincingness of deployment in question: a prediction mechanism proved in, e.g., industrial plumes forecasting in Ramadan et al.'s (2024) study can be reliably expected to provide similar early warning improvements once deployed in the context of oil spills, gas flaring, and pipeline leakage that characterize the Niger Delta.

➤ *Improved Regulatory Compliance*

Predictive systems happen to provide some strange but useful additional capacity of improving regulatory compliance through providing continuous, verifiable and, depending on the architecture used, even tamper-proof evidence regarding the environmental situation. Gade (2023) illustrates that by presenting an example of how blockchain secured environmental data provides a verifiable audit trail, applicable not only to Environmental Impact Assessments, but also to emerging carbon credit markets, and addresses the old Nigerian issue of dubious and arguable self-reported industrial emissions. This blockchain-based approach is not limited to environmental data in the Nigerian literature: Akazue et al. (2023) apply an almost identical blockchain-based technology model in the context of palliative food distribution. Okumoku-Evoro et al. (2025) extend the same fundamental approach into blockchain-based internet identity management systems, indicating that the technical components for tamper-proof verifiable environmental data trail in the Niger Delta are already "there" in local research, even though they have not been implemented in the environmental governance in application form yet. Rehman et al. (2021) have also found that firms with developed Environmental Management Control Systems exhibit significantly better ecological performance, so that is another point supporting the idea of a potential of predictive, data-driven monitoring as the tool to transform environmental compliance from a post-incident, punitive activity into a continuous one, backed up with verifiable data trails.

That change is important for a region, where the credibility of environmental data has been a contested issue between regulators, oil companies, and affected communities. Each side of these debates has questioned impartiality of environmental data gathered and presented or commissioned by stakeholders having commercial and/or political interests in the

matter. Continuous operation of independently verifiable sensor network described in this article provides a plausible technical solution to the problem of impartial factual base in the debates. Nevertheless, such sensor network cannot solve the underlying political and economic conflicts.

➤ *Community Protection*

There are a few reviewed studies showing the link between predictive environmental monitoring and improvements in public health. In particular, Behal and Singh (2024) have observed 12% reduction in emergency-room visits due to respiratory illnesses during the days with peak pollution in the areas with predictive health risk alerting application. Hussain et al. (2020) have reported 35% improvement in localized air quality measurements following the introduction of predictive waste collection route, which prevented bins from overflowing. Okafor et al. (2023), while studying ICT technologies as a means of waste management, have also found improvement in sanitation outcomes through use of digital tracking in addition to traditional manually conducted waste collection. Hence, non-predictive digital solutions are capable of bringing environmental improvements to the communities, if properly applied. Thus, the benefits of predictive environmental governance extend beyond regulatory measures and touch upon health and safety of vulnerable populations, including Niger Delta communities living near the flare sites and pipeline routes.

However, one ought to emphasize that the health benefits of such systems appear to be highest precisely in cases where predictive models are combined with some sort of system of delivering recommendations that people can follow based on predictions made. Behal and Singh's (2024) mobile application that delivers personalized warnings for users who already have certain respiratory problems taking into account the air quality forecasted by the app, and not just measured at the time, exemplifies a design approach that could be very relevant for the Niger Delta area. In other words, a predictive system that delivers its results solely to regulators but never to those communities who will be at greatest risk of being exposed to the pollution essentially disregards the bulk of its public health potential.

➤ *Environmental Accountability*

Moreover, predictive environmental monitoring systems increase the accountability of such practices by making the environmental data easier to access and thus, more transparent to a much larger variety of actors, including both governmental institutions, oil companies, scientists and even the communities themselves. According to Chisom et al. (2024), this is a part of a bigger "data-driven revolution" in conservation and environmental governance, where opening up the environmental data to a greater number of actors is viewed as an indispensable part of the environmental management process and not merely its additional feature. Nonetheless, the extent to which such opening up is going to lead to actual accountability largely depends on how trusting of AI-based systems the communities are. In their paper on the role of emotions in

influencing user trust in AI-based human-like technologies, Okofu et al. (2023) show that user trust in AI-driven systems is greatly influenced by emotional variables. Such a finding bears particular importance for the development of a communication strategy for presenting the predictive environmental data to the residents of the Niger Delta, so that this information could be trusted and utilized. The issue of accountability of predictive environmental data is also analyzed in the accompanying article to this research.

VII. CHALLENGES AND POLICY IMPLICATIONS

➤ *Infrastructure Limitations*

Despite the wealth of empirical successes that the relevant studies have already managed to achieve, there are a number of infrastructural hurdles which consistently prevent effective implementation of the predictive environment monitoring technology in such environments as the Niger Delta. For example, reliable power supply and internet connectivity (which has become increasingly unreliable within vast areas of the region in question) are already a prerequisite for constant data transmission on which predictive solutions rely. According to Almalki et al. (2023), even highly funded smart-city implementations often find it challenging to balance the energy consumption requirements of large-scale sensor networks and actual environmental sustainability, and this issue becomes even more pressing in the absence of stable power grid. Longer-term perspective may improve this issue via evolving mobility infrastructure – according to Okumoku-Evrero et al. (2025), implementation of the 6G wireless infrastructure alongside the IoT devices would result in a significant increase in the bandwidth and reduction of the latency in comparison with current network infrastructure, but these benefits are still yet to come in practical terms for the Niger Delta regions.

Another factor, which makes the infrastructure issue more challenging in the Niger Delta is the geography of the region which is not always completely reflected in the international literature. Indeed, most of the evidence that exists on the topic was gathered from the urban areas linked to stable energy grid of various countries such as Asia, Europe and North America. In the case of the Niger Delta, however, presence of the creeks, swamps and periodically flooded territories implies that the installation of the fixed sensors and their continuous maintenance are more challenging operations compared to those that take place in the more easily accessible urban areas described in the literature. Thus, in the implementation strategy for the Niger Delta it should be taken into account that maintenance expenses will have to be higher on a per-node basis, there will have to be multiple options for alternative connectivity (from cellular networks, to satellite and mesh networks) and the existence of a maintenance team that could access remote areas via boats.

➤ *Data Governance*

With the rise of environmental sensors, important issues in data governance arise, especially concerning ownership

rights, access entitlements, and standards under which environmental data ought to be shared among government authorities, oil companies, academic research institutes, and communities. Kozlowski et al. (2023) suggest the meta-evaluation framework built upon the following pillars: scalability, data integrity, energy efficiency, latency, and cost-effectiveness. It is claimed that without standardized evaluation criteria, many potentially robust monitoring systems would be much harder to compare, replicate, and implement in other jurisdictions. The problem of the lack of standardized data evaluation criteria becomes particularly urgent in the context of Nigeria – the federal country where environmental monitoring is distributed among federal, state, and local regulators. Such problems are nothing new. Okumoku-Evrero (2018), analysing database duplicity in Nigeria, shows that the absence of harmonized standards of data collection within public institutions results in fragmented and duplicated databases, which are not easily comparable. Thus, any future environmental data platform would need to consider it and build around it, rather than assuming that such issues would be solved eventually.

One of the related problems is connected to the management and control of predictive models used for analysis of collected data, separately from raw sensor data that they use. When predictive models are owned and developed by private commercial organizations, including oil companies, there may be certain concerns about their transparency, auditability, and potential conflict of interest. Gade's (2023) blockchain-based solution for ensuring data integrity and security is one of possible answers to the problem, while Okumoku-Evrero et al. (2025) provide another local example in the form of blockchain-based internet identity management system. However, as Kozlowski et al. (2023) emphasize, technological solutions to the governance problem could work only if they were built into certain institution- and legal-based framework. In other words, data governance is a policy problem that technology could facilitate.

➤ *Cybersecurity Concerns*

As environmental monitoring networks become increasingly interconnected and relevant to regulatory and commercial decision-making processes, they also become increasingly tempting targets for data tampering or sabotage, especially in a region where environmental data is commercially significant. Ullo and Sinha (2020) identify data security as the greatest constraint for the adoption of IoT-based environmental sensing systems by the public sector, which corresponds quite well to the integrity solution presented in Gade (2023), but... There is always a tradeoff, right? The cost being increased transactional complexity and, according to Gade's assessment, limited scalability when the data from IoT arrives in velocity. In general, Nigerian research into the security of IoT systems tends to reiterate the risks involved. Ikem and Akazue (2025) present a model for IoT-based prevention of data misuse and theft. In a second research article, a data theft prevention architecture for an IoT-based medical

information system (Ikem & Akazue, 2025). These works suggest that Nigerian IoT systems, whether environmental or not, remain vulnerable to unauthorized data access in the absence of dedicated security solutions, which makes the network threats as significant in addition to the vulnerabilities of the devices themselves. Yoro et al. (2025) introduce an adaptive Distributed Denial-of-Service detection method for software-defined SIP-VoIP networks using transfer learning with a boosted meta-learner. An adaptive intrusion detection solution based on machine learning would be precisely the kind of feature that an environment-based, software-defined and IP-networked distributed sensor network would require in order to maintain its availability and reliability under deliberate attack.

➤ *Institutional Readiness*

Perhaps the greatest barrier identified across the literature is not technical, but rather institutional. Rahaman (2025) and Hoang et al. (2022) alike emphasize the requirement of regulators to have technical capacity, legal authority and willingness to act on the basis of machine-produced predictions. For Nigeria, this means targeted reskilling of environmental regulatory staff, legal standing of machine-produced environmental evidence and institutional feedback loops to translate the predictions into regulatory obligations. The experience of the broader Nigerian public sector in maintaining complex always-on digital platforms is illustrative too, since Malasowe et al. (2023), when analysing an adaptive learner-centered computer-based testing platform with secured fault tolerance and resumption for Nigerian universities, reveal the technical feasibility as well as the large organizational burden of making sure that such systems will operate reliably.

Organizational readiness is especially important in the Niger Delta context, since there are a variety of stakeholders with a stake in the environmental impact who have some incentive for controlling the transparency and interpretation of the predictive environmental data - federal and state regulators, multinational and local oil companies, communities hosting those operations, and civil society organizations. Rehman et al. (2021) report in a broader corporate sustainability setting that environmental management systems are effective only when data-driven formal controls are supported by informal and cultural organizational buy-in. The same is true, likely in a more pronounced form, in a multi-stakeholder regulatory setting of the Niger Delta, where the technical capacity is not a substitute for real organizational and political commitment to acting on the predictions.

VIII. CONCLUSION

This literature review, which features relatively uniform conclusions, demonstrates that IoT-and AI-powered environmental monitoring systems can provide predictive accuracy in the range between 90% to 95% in air, water, and soil contexts. Moreover, they increase warning lead times from a couple of hours to several days, and they result in tangible public health, regulatory, and environmental benefits.

Importantly, those capabilities are no longer theoretical and experimental; on the contrary, they have already been implemented successfully on an operational basis in multiple international settings, and to some extent even in Nigeria as well (Ukadike et al., 2023; Onyagu et al., 2024). At that, their implementation is supported by the domestic scientific and research base of IoT technologies, machine learning models, and cybersecurity issues, including surveillance of oil spills, construction of smart city infrastructure, agricultural IoT systems, blockchain-based data security and integrity, and device level cybersecurity (Akpayibo et al., 2022; Ihama et al., 2023, 2025; Akazue et al., 2023, 2024; Ikem & Akazue, 2025; Yoro et al., 2025). Nevertheless, that scientific and research base has yet to be integrated into the single environmental governance platform. What is lacking in the Niger Delta area in particular is precisely the lack of a properly integrated governance framework using those technologies.

On the basis of the literature review conducted above, the present article suggests a certain four-stage approach to the transition of Nigeria, and of the Niger Delta in particular, towards predictive environmental governance. The first step will be the phased deployment of low-cost, solar-powered IoT sensor networks in priority pollution corridors, starting with the high-risk oil infrastructure and flaring sites, using field-proven, regionally tailored platforms such as SWROSS surveillance system (Akpayibo et al., 2022).

The next stage will be the integration of proven machine learning architectures, especially ensembles and LSTM-based models, which, according to all reviewed literature, provide the best prediction results into the centralized cloud-based environmental data platform that can be accessed by the regulators relatively easily.

At the third stage, the emphasis is shifted to data governance and cybersecurity protocols, including standardized agreements on data exchange among the government, oil companies and independent scientists. Also required are device and network-level security measures suggested by Ikem & Akazue (2025) and Yoro et al. (2025).

The fourth and final stage entails building institutional capacity among Nigeria's environmental regulators based on operational lessons learned in sustaining other complex Nigerian digital public systems (Malasowe et al., 2023), such that predictions trigger timely enforcement actions rather than simply being a record of past damages, which seems to be how many environmental data in Nigeria still serve.

Overall, these four steps offer a practical and evidence-informed path for Nigeria to shift its environmental governance regime from a reactive mode, which has characterized Nigeria for decades, towards a predictive and proactive one, something that the technologies discussed here have already proven possible to achieve.

In addition, this paper also contributes to current academic debates around smart environmental governance, digitalization of environmental regulation, and environmental informatics in developing countries contexts, as it suggests that the evidence for smart predictive environmental governance no longer needs to rely on speculations and futuristic technologies but rather a substantial body of diversified methodological evidence drawn from international experience and from increasingly mature Nigerian research base in IoT, machine learning, and cybersecurity.

Therefore, what is left to discuss at this point is no longer a problem of technological feasibility but rather political will, institutional design, and funding, which the companion paper associated with this research focuses more on, especially in regard to community participatory and multi-stakeholder aspects of sustainable environmental governance in oil producing regions.

REFERENCES

- [1]. Akazue, M. I., Edeki, E. J., Ogeh, C. O., & Ufiofio, E. (2023). Application of blockchain technology model in food palliative distribution in developing countries. *FUPRE Journal of Scientific and Industrial Research*, 7(2), 81–90.
- [2]. Akazue, M., Pirah, L. O., Ogeh, C., & Otegbalor, S. A. (2024). Development of enhanced agricultural greenhouse systems for developing countries. *Nigerian Journal of Science and Environment*, 22(1), 68–77. <https://doi.org/10.61448/njse221246>
- [3]. Akpoyibo, T. P., Akazue, M. I., & Ukadike, I. D. (2022). Development of a floating surface water robotic oil spillage surveillance (SWROSS) system. *Global Scientific Journal*, 10(11), 2214–2230.
- [4]. Almalawi, A., Alsolami, F., Khan, A. I., & Alkhathlan, A. (2022). An IoT based system for magnify air pollution monitoring and prognosis using hybrid artificial intelligence technique. *Environmental Research*, 203, 111871.
- [5]. Almalki, F. A., Alsamhi, S. H., Sahal, R., Hassan, J., et al. (2023). Green IoT for eco-friendly and sustainable smart cities: future directions and opportunities. *Mobile Networks and Applications*, 28, 123–145.
- [6]. Alqahtani, O. S., & Kshirsagar, P. R. (2024). Artificial intelligence and machine learning for environmental monitoring and management: A comparative benchmarking analysis using public datasets. *International Journal of Online and Forensics Systems*, 3(1), 1–15.
- [7]. Amah, C. C., et al. (2024). Assessment of petroleum hydrocarbon contamination in the Niger Delta: Implications for environmental control mechanisms.
- [8]. Asghar, T., Amber, K., Arqam, M., Liaqat, M., et al. (2025). AI-enabled IoT architecture for comprehensive environmental monitoring and prediction. *Spectrum of Knowledge*, 1–25.
- [9]. Asha, P., Natrayan, L., Geetha, B. T., Beulah, J. R., et al. (2022). IoT enabled environmental toxicology for air pollution monitoring using AI techniques. *Environmental Research*, 205, 112574.
- [10]. Atonuje, O. E., & Egwali, A. O. (2023). An improved automatic context summary generator system using data-mining. *Nigerian Journal of Science and Environment*, 21(2), 621–637.
- [11]. Azanor, J., Akazue, M. I., & Okpomi, A. P. (2025). Enhanced deep learning model for vital signs real-time monitoring. *Iconic Research and Engineering Journals*, 9(4), 1242–1252.
- [12]. Baranwal, A. (2025). IoT-based environmental sensing solutions for smart city monitoring. *Smart City Insights*, 1–22.
- [13]. Behal, V., & Singh, R. (2024). An intelligent air monitoring system for pollution prediction: a predictive healthcare perspective. *The Computer Journal*, 1–18.
- [14]. Bellini, P., Nesi, P., & Pantaleo, G. (2022). IoT-enabled smart cities: A review of concepts, frameworks and key technologies. *Applied Sciences*, 12(3), 1607.
- [15]. Chinnappan, C. V., John William, A. D., Nidamanuri, S. K. C., et al. (2023). IoT-enabled chlorine level assessment and prediction in water monitoring system using machine learning. *Electronics*, 12(4), 856.
- [16]. Chisom, O. N., Biu, P. W., Umoh, A. A., et al. (2024). Reviewing the role of AI in environmental monitoring and conservation: A data-driven revolution for our planet. *World Journal of Advanced Research and Reviews*, 21(2), 1–18.
- [17]. Gade, P. K. (2023). AI-driven blockchain solutions for environmental data integrity and monitoring. *NEXG AI Review of America*, 1–22.
- [18]. Hoang, T. D., Ky, N. M., Thuong, N. T. N., Nhan, H. Q., et al. (2022). Artificial intelligence in pollution control and management: Status and future prospects. *Process Safety and Environmental Protection*, 168, 1–15.
- [19]. Hussain, A., Draz, U., Ali, T., Tariq, S., Irfan, M., Glowacz, A., et al. (2020). Waste management and prediction of air pollutants using IoT and machine learning approach. *Energies*, 13(15), 3930.
- [20]. Ihama, E. I., Akazue, M. I., & Amenaghawon, V. A. (2025). Vehicular movement prediction via supervised vector machine. *FUPRE Journal of Scientific and Industrial Research*, 9(1), 206–215.
- [21]. Ihama, E. I., Akazue, M. I., & Obahiagbon, K. O. (2025). A survey of smart city development and the role of Internet of Things. *FUPRE Journal of Scientific and Industrial Research*, 9(1), 28–37.
- [22]. Ihama, E. I., Akazue, M. I., Omede, E., & Ojie, D. (2023). A framework for smart city model enabled by Internet of Things (IoT). *International Journal of Computer Applications*, 185(6), 6–11.
- [23]. Ikem, O. C., & Akazue, M. I. (2025). Data misuse and theft protection model in internet of things devices. *Scientia Africana*, 24(2), 277–282.

- [24]. Ikem, O. C., & Akazue, M. I. (2025). Data theft protection architecture for Internet of Things (IoT)–integrated medical information system. In *Proceedings of the 8th Faculty of Science International Conference (FOSIC 2025)* (pp. 290–299). Delta State University.
- [25]. Kozłowski, T., Noran, O., & Trevathan, J. (2023). Designing an evaluation framework for IoT environmental monitoring systems. *Procedia Computer Science*, 219, 1680–1688.
- [26]. Malasowe, B. O., Akazue, M. I., Okpako, E. A., Aghware, F. O., Ojie, D. V., & Ojugo, A. A. (2023). Adaptive learner-CBT with secured fault-tolerant and resumption capability for Nigerian universities. *International Journal of Advanced Computer Science and Applications*, 14(8).
- [27]. Manduva, S. (2020). Edge-fog-cloud architectures for real-time environmental data processing.
- [28]. Narayana, T. L., Venkatesh, C., Kiran, A., Kumar, A., Khan, S. B., et al. (2024). Advances in real time smart monitoring of environmental parameters using IoT and sensors. *Heliyon*, 10(1), e23841.
- [29]. Obire, E. V., Akazue, M. I., & Okumoku-Evrero, O. (2026). Integration of real-time occupancy detection module and security encryption standards for an IoT-based smart distribution metered system. *International Journal of Research and Scientific Innovation*, 13(4), 730–739. <https://doi.org/10.51244/IJRSI>
- [30]. Okafor, N. U., Ingle, R., Matthew, U. O., & Saunders, M. (2024). Assessing and improving IoT sensor data quality in environmental monitoring networks.
- [31]. Okafor, U. O., Okeke, A. N., & Okumoku-Evrero, O. (2023). Information and communication technology as an effective tool in waste management. *Journal of Technical Education and Research Development*, 7(2).
- [32]. Okofu, S., Anazia, E. K., Akazue, M., Ogeh, C., & Ajenaghughure, I. B. (2023). The interplay between trust in human-like technologies and integral emotions: Google Assistant. *Kongzhi yu Juece/Control and Decision*, 38(1), 809–828.
- [33]. Okumoku-Evrero, O. (2018). Database duplicity in Nigeria: Any hope for harmonization. *Multidisciplinary Journal of Scientific Research and Education*, 2(11).
- [34]. Okumoku-Evrero, O., Atonuje, O. E., Ejenarhome, O. P., & Edeki, E. J. (2025). Integration and impact of 6G technology on IoT devices. *GAS Journal of Engineering and Technology*, 2(7), 15–24. <https://doi.org/10.5281/zenodo.17164237>
- [35]. Okumoku-Evrero, O., Atonuje, O. E., & Esosuakpo, O. T. (2025). Blockchain-based internet identity management systems. *International Journal of Advanced Science and Research*, 10(2), 10–17.
- [36]. Okumoku-Evrero, O., Oseh, V., & Salmon, I. A. (2017). Use of software agents in e-commerce: Benefits and applications. *International Journal of Advanced Engineering and Management Research*, 2(1).
- [37]. Onyagu, C. L., Akawuku, I. G., Joshua, J., & Okonkwo, C. (2024). Integration of gas and ultrasonic sensors for monitoring air quality and smart waste bin levels determination: An IoT illustration in solid waste management.
- [38]. Polymeni, S., Athanasakis, E., Spanos, G., Votis, K., et al. (2022). IoT-based prediction models in the environmental context: A systematic literature review. *Internet of Things*, 19, 100544.
- [39]. Popescu, S. M., Mansoor, S., Wani, O. A., Kumar, V., Sharma, A., et al. (2024). Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management. *Frontiers in Environmental Science*, 12, 1336088.
- [40]. Rahaman, T. (2025). Smart environmental monitoring systems for air and water quality management. *American Journal of Advanced Technology and Engineering Solutions*, 1(1), 1–19.
- [41]. Ramadan, M. N. A., Ali, M. A. H., Khoo, S. Y., Alkhedher, M., et al. (2024). Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment. *Process Safety and Environmental Protection*, 182, 456–478.
- [42]. Ramani, D. R., & Sujitha, B. B. (2025). Smart environmental monitoring systems: IoT and sensor-based advancements. *Environmental Monitoring and Assessment*, 197(3), 112–135.
- [43]. Rehman, S. U., Bhatti, A., Kraus, S., & Ferreira, J. J. M. (2021). The role of environmental management control systems for ecological sustainability and sustainable performance. *Management Decision*, 59(9), 2217–2237.
- [44]. Syed, A. S., Sierra-Sosa, D., Kumar, A., & Elmaghraby, A. (2021). IoT in smart cities: A survey of technologies, practices and challenges. *Smart Cities*, 4(2), 429–490.
- [45]. Ukadike, I. D., Akazue, M., Omede, E., & Akpoyibo, T. P. (2023). Development of an IoT-based air quality monitoring system. *FUPRE Journal of Scientific and Industrial Research*, 7(4), 53–62.
- [46]. Ukadike, I.D., Okpako, A.E., & Isitor, N.D. (2024). Development of an iot-based humidity, temperature, and air quality monitoring system - *Scientia Africana*, Vol. 23 (No. 1). Pp 131-142
- [47]. Ullo, S. L., & Sinha, G. R. (2020). Advances in smart environment monitoring systems using IoT and sensors. *Sensors*, 20(11), 3113.
- [48]. Yoro, R. E., Okpor, M. D., Akazue, M. I., Okpako, E. A., Eboka, A. O., Ejeh, P. O., et al. (2025). Adaptive DDoS detection mode in software defined SIP-VoIP using transfer learning with boosted meta-learner. *PLoS ONE*, 20(6), Article e0326571. <https://doi.org/10.1371/journal.pone.0326571>