

Environmental Monitoring in Oil-Producing Regions: Integrating IoT, Machine Learning, and Community Participation for Sustainable Development in the Niger Delta

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ABSTRACT

Technology alone cannot resolve the environmental crisis in oil-producing regions such as the Niger Delta, where oil spills, gas flaring, and industrial discharge have degraded ecosystems, endangered public health, and eroded community trust. This article presents a meta-analytic synthesis of over seventy studies (2020–2025) on IoT, machine learning, and participatory approaches to environmental monitoring, synthesising technological and participatory literatures into a single, integrated framework for sustainable development. It documents the scale of degradation from oil spills, gas flaring, and water contamination; catalogues structural limitations, namely delayed reporting, weak coordination, and limited community involvement; and synthesises the performance of IoT- and ML-enabled monitoring architectures reported across the corpus. It makes the case for community-based monitoring as a necessary complement to sensing, arguing that citizen participation, transparency, and environmental justice are structural requirements for legitimacy. It concludes with an integrated, multi-stakeholder framework and policy recommendations for government, oil companies, researchers, and communities.

Keywords: environmental monitoring, oil-producing regions, IoT, machine learning, community participation, environmental justice, Niger Delta.

INTRODUCTION

Oil-producing regions occupy a paradoxical position in the political economy of development: they generate the fiscal resources on which national economic growth largely depends, while at the same time bearing an imbalance share of the ecological and human costs of that growth. Nigeria's Niger Delta exemplifies this paradox with unusual severity. Since the discovery of commercial quantities of crude oil in the region in 1956, decades of extraction activity have generated high national revenue while leaving behind a legacy of oil spills, gas flaring, pipeline leakages, and industrial discharge whose cumulative ecological and human toll remains only partially documented (Amah et al., 2024). This toll has never been purely environmental in character; Bisina (2005), writing on oil and corporate recklessness in the region, documents how decades of extraction proceeded alongside a pattern of corporate disregard for community welfare that helped entrench the very distrust between industry, government, and residents that any future monitoring system must now work to overcome.

This article approaches the environmental crisis from a deliberately synthetic standpoint. Many of the existing literature on environmental technology in oil-producing regions is written either from a narrowly technical perspective, emphasising sensor accuracy and algorithmic performance, or from a narrowly socio-political perspective, emphasising environmental justice, community rights, and institutional failure, with comparatively few contributions trying to hold both strands in a single analytical frame. By conducting a meta-analytic synthesis that explicitly combines both the technical performance characteristics and the participatory design features of the reviewed literatures, this article aims to demonstrate empirically, rather than merely asserting the

norms, that these two strands of the literature are in fact mutually reinforcing rather than competing priorities for environmental monitoring in oil-producing regions.

Environmental Crisis in the Niger Delta

Recent environmental assessments keep on identifying thousands of contaminated sites across the Niger Delta, a scale of degradation that reflects both the intensity of decades of hydrocarbon extraction and the persisting weakness of the monitoring and remediation mechanisms meant to contain its impact (Amah et al., 2024). This degradation is not evenly distributed; it is concentrated in and around specific oil infrastructure corridors, pipeline rights-of-way, flow stations and flare sites, with the communities located nearest to these infrastructures being the most affected and bearing the heaviest and most immediate burden. The persistence of this crisis across multiple decades and successive regulatory regimes shows that the problem is not merely one of insufficient environmental awareness or policy intent, but of a monitoring and enforcement architecture that has consistently failed to keep pace with the scale, speed, and geographic dispersion of pollution events in the region. This institutional failure has technical and social consequences: Bisina (2001), examining conflict and conflict resolution in the Niger Delta through the Bayelsa experience, and Bisina (2021), in a later doctoral study of postamnesty youth violence in the region, both trace a direct line from unresolved environmental grievance to sustained community-level conflict, stressing that a monitoring architecture perceived as unresponsive to environmental harm is not just a technical shortfall but a contributing factor in the region's wider pattern of unrest.

Need for Integrated Monitoring Approaches

There is now a considerable amount of literature suggesting that dealing with the problem will necessitate using an approach that integrates the technological ability of the sensors with the involvement of the community rather than regarding these two strategies as competing options. This idea goes against an older line of the environmental technology literature according to which the implementation of sensor technologies was perceived as a solution in itself. According to Santos and Carvalho (2025), the development of participatory environment management has led to the realization that the use of artificial intelligence should aim not at replacing human judgement but at widening the scope of participants in the process of environment management, which includes, among other things, the communities who suffer because of this problem. It should be noted that the integration orientation of this article aligns with a broader tendency visible in the IoT literature of Nigeria, where sensors created to solve certain problems (for instance, enhanced agricultural greenhouse systems developed by Akazue et al., 2024) are seen not as technical solutions but as parts of a bigger picture.

METHODOLOGY

This article employs a meta-analytic synthesis method to the literature on the topic, going beyond simple review of the literature to systematically compile and compare the methodological details, performance results, and limitations of more than seventy articles on environmental monitoring facilitated by the use of Internet-of-things technology and machine learning techniques from 2020 to 2025. Similarly to other meta-analytical works in the areas of environmental and technology research (see Polymeni et al., 2022; Kozłowski et al., 2023), all papers were coded into five dimensions: (i) the environmental domain (air, water, soil or multi-domain) to which they refer; (ii) the technical architecture (the type of sensors used, communication protocol, machine learning or deep learning algorithm employed); (iii) the quantitative result of performance (accuracy, RMSE, R-squared value, or percentage improvements in accuracy, where reported); (iv) the level of community or stakeholder involvement; and (v) stated limitations.

This coding scheme allows for two complementary forms of synthesis. The first is a conventional meta-analytic Comparative analysis of the quantitative performance results from different studies within the same environmental domain, based on the precedent set out in the meta-evaluation methodology from Kozłowski et al.'s (2023) study on IoT environmental monitoring designs where different designs were compared against each other in terms of the five pre-defined pillars of system performance: scalability, data integrity, energy efficiency, latency, and cost effectiveness. Second is thematic meta-synthesis of the qualitative and governance findings presented in the reviewed corpus, especially findings related to community involvement, transparency of

process, and institutional cooperation which cannot be numerically aggregated but may still be subject to systematic comparative study. Table-based summarisation, used in this article, which is essentially the same type of data-mining based automated summarisation technique suggested by Atonuje and Egwali (2023) in the context of the parent thesis that this article is based on.

However, it should be noted about this work's methodological aspect that in the framework of this kind of review the heterogeneity of the underlying corpus is a factor which should be taken into account. Unlike the case of a typical clinical meta-analysis where all studies are characterized by identical measures of outcomes and experiment design, when conducting a technological systematic review the literature dealing with Internet of Things and machine learning application to environmental research can belong to various domains of environment, geographic settings and reporting styles, and hence straightforward numerization of the data like accuracy rates in the analyzed research papers might well overlook many important nuances related to how exactly the values in question are calculated. It means that in the framework of the provided synthesis in Section 5 the ranges of performances and clusters of results in the particular environmental domains are utilized as the basis of comparison as opposed to the use of effect size, which is a more conservative but methodologically justified choice due to heterogeneity of the underlying corpus, similarly to how Polymeni et al. (2022) do.

Environmental challenges in oil-producing regions

Oil spills

Despite various forms of pollution accompanying the development of Niger Delta oil fields, the oil spills remain the main threat to the region's environment and the ecological damage caused by them continues to persist. As a result of contamination with spilled crude oil, the activity of microorganisms in soil becomes suppressed; the process of decomposing organic matter slows down; nutrient cycle becomes disturbed; agriculture stops being sustainable in such areas. Besides, the heavy metal content (lead, nickel, vanadium, and barium) becomes accumulated in soils over decades, getting into food chain of animals. Therefore, the impact on health of humans and environment continues for many years or even decades after the spill has happened and is not detected with the help of traditional one-time monitoring technologies. The SWROSS – floating surface water robotic oil-spillage surveillance system designed specifically for creek terrain in Niger Delta by Akpoyibo et al. (2022) is an example of existing locally-engineered solution of at least the problem of detection of this issue.

Regarding the soil-specific part of the issue, a number of predictive modelling studies have gained popularity overseas despite being relatively less widespread in the Niger Delta itself. For instance, the study conducted by Wang et al. (2020) proved the superiority of the Random Forest models' performance compared to that of linear regression as far as mapping of heavy-metal concentration in soils is concerned due to the complexity of relations between various soil properties that need to be captured, while Zhao et al. (2023) obtained similar results by building XGBoost models to predict hotspots of heavy metals in the Pearl River Delta region in China. Therefore, the methodological approach to mapping and predicting the legacy of soil contamination caused by Niger Delta oil spills becomes clear with respect to developing the necessary local soil sampling and sensors' infrastructure.

Gas Flaring

Gas flaring is still widely practiced in the Niger Delta despite numerous promises to eliminate the practice for many years already. Continuous burning of associated natural gas produced during crude oil production entails emissions of large quantities of various toxic substances, greenhouse gases and particulate matter right into the atmosphere often in very close proximity to densely populated residential areas built or relocated because of oil infrastructure. Chronic, not acute pollution caused by gas flaring is more difficult to detect with conventional and sporadic environmental monitoring techniques compared to oil spills and thus represents an important advantage for continuous IoT-based air quality sensing.

Water Contamination

Oil spills into rivers and creeks, the discharge of sewage and other waste water from industrial enterprises, as well as the illegal artisanal refining, driven by the economic situation, are all the main causes of water

contamination in the Niger Delta region. As the network of water bodies in the Niger Delta is highly developed with many creeks and estuaries, any form of water pollution tends to spread over great distances very quickly, affecting fishing and irrigational activities in different places, a trend discussed in Essamlali et al. (2024) in the context of advanced deep-learning models.

The tidal and estuarine character of much of the Niger Delta's hydrology further complicates water quality monitoring relative to the inland river and reservoir environments that form the subject matter for most of the research on predictive monitoring frameworks considered here. Indeed, Deng, Chau and Duan (2021) find that the degree to which their marine water-quality prediction framework performs accurately varies significantly with extreme storm and tidal conditions, exactly the type of environmental conditions in which the spread of contamination from Niger Delta pollution will be both highest in degree and most relevant for predicting public health risk in the affected areas.

Public Health Impact

In terms of the overall health impact of oil spills, gas flaring, and other forms of environmental contamination within the Niger Delta, effects can range from short- and long-term respiratory illnesses caused by exposure to particulates and gases released in oil and gas activities through waterborne illnesses caused by the pollution of drinking water, along with long-term impacts to public health and nutrition associated with reduced agricultural and fishery yields. Subramaniam et al. (2022), in their own narrative review of artificial intelligence and the monitoring of environmental public health outcomes, suggest that the ability to forecast environmental public health impacts requires that technical environmental health monitoring frameworks be integrated directly into a public health response framework that can take appropriate action based on the predictions made from monitoring technology; this observation holds especially well for any monitoring framework used in the Niger Delta. The technical framework required – ongoing, near-real time forecasting using a stream of continuous data – is similar in principle to the use of a deep learning architecture to predict and monitor patient vital signs, as described by Azanor, Akazue, and Okpomi (2025).

In Behal and Singh's (2024) analysis of air quality alerts in Indian cities, use of an application-based air pollution prediction tool was able to reduce emergency room visits on high-pollution days in communities where the technology was implemented by 12%. It is important to note the transferability of this intervention model to the Niger Delta precisely because the advanced air quality monitoring does not depend on advanced health care technology but simply on the prediction capability and the means to communicate the health risks to community members.

Limitations of Existing Monitoring Systems

Delayed Reporting

The first consistent limitation noted in meta-analytic research is that of delayed feedback in terms of results obtained by non-predictive environmental monitoring solutions. Being based on manual field observations and lab analysis, these types of solution deliver their results from several days up to several weeks after the pollution itself occurred. This makes it difficult to implement proper remediation efforts in a timely manner, as well as reduce the reliability of the evidence in terms of regulation or prosecution in case of need to address such situations. In contrast, Nigeria-specific IoT-based solutions described in this paper, Ukadike et al. (2023), Ukadike et al. (2024) and Onyagu et al. (2024), demonstrate improved approach to providing feedback via threshold alerting systems, but still do not provide predictive nature characteristic to some of the systems discussed in the current literature.

Weak Institutional Coordination

Another common issue associated with such projects lies within fragmented responsibility among different entities within government and different agencies in charge of regulating various issues related to environment, such as oil spills, air quality, water quality and general environment protection. Being separated into various governmental, federal, sectoral and state agencies which utilize different information systems, formats of

reporting and priorities, the problem of fragmentation greatly complicates implementation of unified platform. Kozłowski et al. (2023) suggest that standardization of assessment can solve this problem at least in part. However, in the process of addressing this challenge one should realize that it is not of technical nature, but rather political and organizational. In particular, it can be stated in the context of this issue, as Okumoku-Evrero (2018) discusses fragmentation of database within Nigeria more generally.

In the particular instance of the Niger Delta, this situation is aggravated further by the presence of yet another group of non-state actors: the multi-national and indigenous oil companies who have an active presence there, and whose internal environmental monitoring systems often do not at all interface with, let alone connect with, official data sources maintained by governments. The upshot is a monitoring environment where potentially inconsistent information about the same geography within the same timeframe can flow through multiple, disconnected data streams without any ready means of reconciling them with each other, a problem that the sort of meta-analyzed and truly integrated monitoring system architecture proposed in Section 7 below aims to solve. Technological advances in basic connectivity systems – e.g., in the form of integrating next-gen networks with Internet of Things devices, as discussed by Okumoku-Evrero, Atonuje, Ejenarhome, and Edeki (2025) – might eventually help mitigate the problem of connecting these disparate agency systems, though the issue itself is more institutional than technological.

Limited Participation of Affected Communities

Among many of the limitations observed throughout this meta-analysis, perhaps the most important one – and certainly the most pertinent one to this article’s central arguments – is the insufficient degree of participation on the part of communities affected by environmental degradation in the process of designing, implementing, and interpreting such monitoring systems. Most of the technical literature reviewed for this study describes a rather linear architecture of environmental monitoring systems where the flow of data goes from sensors to cloud-based storage systems and to regulation dashboard in one stream only, without allowing for any input or feedback from local communities. As Santos & Carvalho (2025) note, this “top-down” architecture is an inherent feature of contemporary environmental management that systematically precludes valuable community insights and information from participating in the process.

The implications of such a technical design decision run deeper than just questions of procedural justice. Monitoring sensor deployment done without community consent risks systematically under-sampling the creeks, farmlands, and fishing spots identified by communities themselves as most impacted by pollution, whereas threshold settings done on entirely technical or regulatory criteria may neglect the unique set of vulnerabilities, such as dependence on a specific fishing ground or a specific source of drinking water, that dictate which pollution episodes carry significance for each community in terms of their impact on people’s wellbeing. As observed by Bisina (2021) in her work on postamnesty youth violence in the Niger Delta, the communities who feel themselves left out of decisions related to their immediate environment experience noticeably higher levels of conflict and unrest compared to those that feel engaged. Such an analysis suggests that limited community involvement acts not just as a moral failing but as a technical failure of monitoring system design.

The Promise of IoT and Machine Learning: A Meta-Analytic Synthesis

The aggregation of performance outcomes reported across the reviewed literature shows a very clear pattern of strong technical performance across all examined environmental dimensions. When it comes to air pollution prediction, accuracy rates consistently cluster around the low-mid nineties percent mark, as is shown by a 92.4% figure reported by Alqahtani and Kshirsagar (2024), a 94.8% figure reported by Almalawi et al. (2022), as well as 92% precision in AQI spikes prediction reported by Behal and Singh (2024). With water quality prediction performance also being extremely high, as can be seen in a reported 95.1% rate of water pollution detection by Alqahtani and Kshirsagar (2024), 0.94 R-squared value for chlorine-level prediction by Chinnappan et al. (2023), 93.5% accuracy in potability classification by Bhardwaj et al. (2022), as well as 91% accuracy in seasonal forecasting by Rahu et al. (2023). Overall, meta-analysis reveals unambiguous results: the accuracy of today’s IoT-ML monitoring systems is sufficient for regulatory usage across the board. Lighter classical predictive modeling is very much present in this picture as well, with Ihama, Akazue, and Amenaghawon (2025) demonstrating the use of Supervised SVM for vehicular movement prediction.

Moreover, the reviewed corpus has evidence on substantial and quantifiable benefits related to improved environmental or operational results downstream from prediction. In particular, Alqahtani & Kshirsagar (2024) report a 41.7% reduction in the number of incidents of illegal logging and a 44.2% reduction in the incidents of water contamination after introducing IoT & AI solutions; Hussain et al. (2020) report a 28% reduction in waste-collection trucks emission and a 35% reduction in the local air pollution, findings that can also be verified via a narrower case, provided by Okafor, Okeke, & Okumoku-Evoro (2023), who investigated the impact of ICT solutions on waste management operations: as was mentioned above, their findings indicate a measurable environmental gain in switching to the digital collection method over the regular method; Manduva (2020) reports that IoT-ML based edge-computation reduces 70% of data transfer volumes and extends batteries' life correspondingly; finally, Baranwal (2025) claims a 15-20% reduction of the local peak pollution through traffic optimization with AI. Therefore, the consistency of the reported 10% or greater results across a broad spectrum of papers and geographical context constitutes, in terms of meta-analytical assessment, a solid empirical basis of the positive environmental and public health impact of IoT & ML-based monitoring.

However, there are other aspects of the meta-analysis of the literature that should be accounted for to get an exhaustive picture of how accurate the solutions are under different circumstances and in different domains. Namely, performance metrics are generally higher in studies performed in well-connected urban areas (for example, Ramadan et al. (2024) and Wei et al. (2025)), and more heterogeneous in the case of remote, poorly connected or ecologically challenging environment, such as in the study of the accuracy of the marine water quality models in the area by Deng, Chau & Duan (2021): according to the authors, its fluctuations are caused by extreme storms and tides. This heterogeneity in the research outcomes is important to take into account when assessing the Niger Delta case, since its ecological situation, characterized by the creek-oriented geography and seasonally changing hydrology. Moreover, the levels of accuracy in the corpus reached a point where one could expect that initial deployments of sensors in the Niger Delta should factor into the design that a process of calibration for a period of time will be necessary prior to achieving the same upper limit of performance as reported internationally. Sensors deployed in the field and designed to perform such calibrations will have to also be developed with the same consideration for their reliability and security, following the example of Obire et al. (2026), who introduced an Internet of Things (IoT) –based smart distribution metered system that combines continuous sensing capabilities with encryption built into its design specifically for unsupervised field deployments.

Another trend arising as a result of meta-analysis is the relation of the level of complexity of predictive models on the accuracy improvement that they bring. While more sophisticated architectures of deep learning models (e.g. Graph LSTM and CNN-LSTM models) tend to give a bit better accuracy figures in comparison with ensemble or regression methods, the actual improvement in accuracy in most cases amounts to a mere two to four percentage points while demanding much more computational and data resources. This finding is also relevant to a design of first-generation Niger Delta sensor network where the primary task is building basic monitoring coverage, a finding that corroborates the findings of the technical analysis conducted alongside this study.

Community-Based Environmental Monitoring

Citizen Participation

Community-based monitoring, where residents of a region actively participate in the collection, verification, and analysis of data, increasingly becomes an important tool used to enhance purely technological sensor monitoring, especially in resource-rich and governance-lacking areas such as the Niger Delta. Participation guarantees that programmes would be culturally adequate and sensitive to the local environment, being able to collect information about seasonal floods, traditional fishing grounds, or even specific signs which community members consider to be the precursors of oil spillage that might not be detected by purely technical means. According to Santos & Carvalho (2025), the combination of the data collected through citizen science with IoT sensor streams makes it possible to visualise how the proposed solutions affect the environment in question, enabling a better and more informed form of public discussions on this issue compared to purely technological or participatory models.

It is unnecessary for each community resident to become a data scientist or sensor maintenance expert to ensure the proper implementation of community participation model. Examples that can be seen in the literature include employing a few community members trained as environmental monitors per settlement responsible for maintaining sensor nodes within the settlement, setting up SMS- or application-based reporting systems that enable residents to report pollution cases that are then verified using sensor information, based on the logic of agent-based and autonomous-monitoring systems found in earlier software-agent implementations in e-commerce (Okumoku-Evrero, Oseh, & Salmon, 2017). Another way includes organising regular reviews of the results obtained through the monitoring process within the community for the verification and evaluation of this data presented in a comprehensible way to them. All these methods of participation have low costs of implementation as compared with the underlying sensor network, thus ensuring that the cost of implementing participation is marginal.

Environmental Justice

The concentration of oil-related environmental harm in specific, historically marginalised Niger Delta communities raises questions about environmental justice that the technical approach to the monitoring problem could obscure. In this respect, environmental justice entails not only issues about equal distribution of harm but also issues about equal distribution of information and means to address it. A monitoring system that delivers its results only to far-away regulatory agencies and corporate HQs rather than to those who are most affected by it perpetuates the same problems related to environmental governance and the existing power inequalities described by Bisina (2005) in historical details through his discussion of the reckless conduct of corporations in the Niger Delta. This question is discussed in wider "data revolution" in conservation and environmental management context by Chisom et al. (2024), who see the need to democratize access to environmental data as a mandatory condition for any environmental monitoring system to work in a historically or politically contested area.

Such an aspect also has some consequences for the credibility of the alert system itself. In cases where communities have been historically exposed to environmental evaluations conducted by official authorities as legitimizing devices for further extraction activities rather than as actual means of protection, a new monitoring and prediction device will most likely be received by the local population with skepticism instead of trust; this skepticism is analyzed by Bisina (2001) for the case of Bayelsa State and directly linked to the unresolved conflicts over oil distribution and the resulting environmental issues. The need to build up such community trust therefore will include building up a reputation of an organization that uses advanced technology and a demonstration of a commitment to transparent actions prior and along with deploying such system, an idea that is consistent with Subramaniam et al.'s (2022) observation about embedding AI-enabled environmental monitoring into the trusted institutional framework in order to achieve full health benefits from the technology. This issue of gaining trust, which is rooted in emotional reasons and not in logical ones, has been explored in other domains apart from environmental one: Okofu, Anazia, Akazue, Ogeh, and Ajenaghughrure (2023), analyzing the relationship between trust of people in human-like technologies and their integral emotions using Google Assistant as an example, show that users' trust of the technologies depends heavily on emotions in addition to technical features of the systems.

Transparency and Accountability

Transparency and accountability mechanisms, including public dashboards, open data policies, and independently are invariably recognised in the reviewed literature as key factors to be satisfied in ensuring trust from the local community in environmental monitoring processes. The solution offered by Gade (2023) in terms of blockchain-based technology to guaranteeing environmental data integrity by making tamper-proof audits is one possible way of overcoming this obstacle. Namely, it would allow for providing communities with access to data from these audit trails as well as to regulators, thus tackling the historical pattern, documented extensively in the Niger Delta region, of community distrust towards environmental monitoring results produced by officials that should allegedly serve the community's interests. Moreover, there are several examples of using similar blockchain-based technologies to ensure public sector accountability in adjacent fields of public service, like food palliatives' distribution (Akazue, Edeki, Ogeh, & Ufiofio, 2023) and online identity management (Okumoku-Evrero, Atonuje, & Esosukpo, 2025). This means that technical basis for development of a

verifiable data audit trail that would also be available to communities is currently available from the Nigerian research pool. In any case, it would be necessary to protect the platform developed for these purposes from such possible problems like misuse and theft of device-level data as described by Ikem and Akazue (2025) and intrusion into the IoT devices as addressed in the adaptive intrusion-detection model suggested by Yoro et al. (2025).

Integrated Framework for Sustainable Development

An integrated framework, which combines both technological advances and participation from various stakeholders, will be proposed in this article, based on the reviewed literature.

It is the various government agencies, including both the relevant federal and state environmental regulators, who will be primarily responsible for providing the legal and institutional framework in which the predictive monitoring data gains regulatory power, for coordinating data standards across the fragmented agency landscape described in Section 4.2, and for translating predictive alerts into time-sensitive enforcement actions. Oil companies, as the primary agents responsible for generating the pollution in question, will need to contribute to the financial cost of building the sensor infrastructure needed for full coverage of the company's territory, as well as accept independent verification of the environmental performance data, as the new audit-trail model by Gade (2023) envisages. Research and technology developers will be expected to adapt the architecture frameworks described through this article, especially those related to device security, as discussed by Ikem and Akazue (2025), and Obire et al. (2026). And, finally, the local communities will not just enjoy but must participate in such an environment-monitoring system – as sources of knowledge about the local ecology and as verifiers of government-provided information about pollution and its effects, as well as the eventual beneficiaries of this entire system.

This interdependence among the roles of all four stakeholder groups represents the central conclusion from this article's meta-analysis. None of these stakeholders, operating alone, can build an environment-monitoring system that is technologically correct, institutionally effective, financially sound, and locally credible. Governmental agencies are unable to build such a system on their own due to their lack of funding and technological expertise; oil companies would be unable to do so on their own due to lack of regulatory legitimacy and public credibility. Researchers cannot develop a system based solely on their expertise; communities cannot finance such a system on their own. The exact interdependence that characterises all four of these roles – this article has sought to highlight and formalize.

POLICY RECOMMENDATIONS

They are the very governmental agencies that will take responsibility for providing the legal and institutional context in which the information becomes regulatory, for unifying standards of data throughout the dispersed institutional landscape mentioned above in section 4.2, and for transforming the alerts issued by such monitoring systems into timely regulatory actions. They are the oil companies, as the main producers of pollution in question, who will have to bear the costs of constructing the sensor networks necessary to provide full coverage of their territories and accept independent verification of their environmental performance data according to the new audit-trail model by Gade (2023). Finally, it will be the researchers who will be required to develop their work within the frameworks described above, particularly in regard to security of the devices, as discussed by Ikem and Akazue (2025), and Obire et al. (2026). And it will be the local communities that are both able and ought to participate in such an environment monitoring system, as providers of knowledge about the local ecology and as verifiers of government-produced knowledge about the pollution and its effects, and the future beneficiaries of this entire system.

Such mutual dependence of all the roles of all these four parties of stakeholders is the fundamental finding in this meta-analysis. Any of them could not build such an environment monitoring system on their own due to their respective limitations – governmental agencies due to lack of money and technologies, oil companies – due to lack of legitimate authority and credibility, researchers – due to lack of experience, communities – due to lack of money. Just exactly such mutual dependence is the essence of the four roles described above.

CONCLUSION

This meta-analytic review of more than seventy studies regarding IoT- and ML-based monitoring highlights the existence of two complementing findings. The first one is that there has been sufficient development within the technological capabilities of environmental monitoring systems that they are practically ready for use in the regions with ongoing environmental crises as their accuracy is estimated in the low-to-mid nineties percentage range. Besides, there is evidence that pollution, efficiency of resource usage and public health have been improved through the implementation of IoT-based solutions, with pollution decrease being between 10% and 50%. On top of that, the literature indicates the importance of community engagement for the successful implementation of environmental monitoring in practice as without that engagement, despite the accuracy of data provided by sensors, there might emerge the same issues that Bisina (2001, 2005, 2021) discusses regarding the failure of the environmental governance in the Niger Delta over decades – lack of trust and empowerment in the community as it has happened before. Therefore, it becomes necessary to combine the IoT technologies and data predictions and analysis with community engagement to make an effective and sustainable environmental management framework.

This article, just like its counterpart focused on the transition from reactive environmental monitoring to predictive, is designed to make a contribution to a literature field regarding environmental informatics and environmental justice in the regions of the Global South that produce oil and have an environmental crisis. While the first article provides an empirical foundation of predictive environmental governance from the point of view of the current technology, this article provides evidence that shows the dependence of its further development in a region like Niger Delta on its deliberate incorporation into governance.

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