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REVIEW

From Data to Decisions: Integrative Frameworks for Environmental Monitoring in the Anthropocene

Fei Zhao

Taiyuan Municipal Ecological Environment Monitoring and Scientific Research Center, Taiyuan 030002, China

ABSTRACT

Environmental monitoring in the Anthropocene is at a pivotal moment from data accumulation towards decision-oriented environmental intelligence. The monitoring systems must be able to integrate multiple data streams and transform these data into actionable, credible and timely knowledge to address the critical issues of rapid climate change, biodiversity loss, pollution, land-use transformation and increasing disaster risks. This review discusses integrative frameworks bringing together the generation of environmental data, analytical synthesis, decision support systems and policy translation. It emphasizes the synergistic use of in situ observations, remote sensing, citizen science, Internet of Things sensors, environmental DNA, bioacoustics and emerging digital platforms. The article examines the role of data fusion, geospatial analysis, statistical modelling, AI, socio-ecological modelling, indicator frameworks, and uncertainty assessment as means to convert observations of diverse nature to usable evidence. It also maintains that interoperability, transparency, institutional capacity, ethical data governance, stakeholder involvement, and environmental justice are equally critical to successful monitoring. The relevance of connecting the outputs of climate monitoring to unambiguous decision pathways is illustrated in applications to climate adaptation, the conservation of biodiversity, pollution control, urban sustainability, water–land systems and disaster risk reduction. The review finds that next-generation environmental monitoring needs to be an adaptive system of knowledge-action that can learn from results, be transparent about uncertainty, and enable accountable governance in a world of dynamic environmental conditions.

Keywords: Environmental Monitoring; Anthropocene; Decision-Support Systems; Data Integration; Adaptive Governance

*CORRESPONDING AUTHOR:

Fei Zhao, Taiyuan Municipal Ecological Environment Monitoring and Scientific Research Center, Taiyuan 030002, China; Email: 13934240705@163.com

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1. Introduction

The Anthropocene is a period marked by unprecedented interactions between human activities and processes of the Earth's system [1]. Climate change, biodiversity loss, land-use transformation, pollution, freshwater depletion, ocean acidification, and increasing disaster risks no longer exist as independent environmental issues, but are symptoms of a rapidly changing socio-ecological system [2]. These pressures occur at a variety of spatial and temporal scales, ranging from local habitat degradation and heat islands to regional droughts, global disruption of the carbon cycle and biodiversity loss at a global scale. In the face of the fast pace of environmental change, information has grown in importance for environmental governance, environmental resource management, environmental public health protection, and climate change adaptation. Environmental monitoring has thus transformed from merely a scientific study of nature into a key tool to support decision-making in an uncertain context [3].

Traditional environmental monitoring has made significant contributions to scientific knowledge and policy-making. Long-term ecological plots, hydrological stations, atmospheric observatories, biodiversity surveys, and pollution monitoring networks have produced irreplaceable data to document environmental changes and anthropogenic disturbances [4]. Many of the traditional monitoring methods, however, were developed for more stable contexts of management, for discipline-specific research questions, or for one-sector goals. They are frequently conducted in a piecemeal fashion, with existing data systems that are incompatible, reporting times that are laggy, and weak linkages between biophysical measurements and socio-economic information. Consequently, there is often a lot of environmental data gathered that is not efficiently converted into decision-making. The "data-to-decision gap" in the Anthropocene has become a key obstacle to successful environmental management [5].

The amount of environmental data in recent years has increased greatly in variety, resolution and quantity. New technologies such as satellite remote sensing, unmanned aerial systems, Internet of Things sensor networks, automated weather stations, environmental DNA, acoustic monitoring, mobile sensing and citizen science platforms have now made it possible to observe environmental conditions with increasingly high spatial resolution and temporal frequency [6]. Meanwhile, the rapid progress of cloud computing, artificial intelligence, machine learning, geospatial analytics, digital twins, and decision-support systems has enabled the embedding of heterogeneous data streams and the ability to turn them into predictive, adaptive and policy-relevant knowledge [7]. These are steps towards moving from environmental assessment to environmental intelligence.

But it's not simply bigger data that leads to better decisions. Environmental datasets frequently lack uncertainty quantification, bias control, comprehensiveness, geographic scale, and geographic representativeness. Remote sensing products can be extensive across spatial domains, but need to be validated with on-the-ground observations [8]. Field measurements may be accurate, but they may not be accurate everywhere. Citizen science can add to participation and coverage, and may add some variation in the quality of data [9]. Machine-learning models can identify complex patterns, but can be opaque, lack transferability, or be based on biased training sets [10]. Further, it is important to note that decision-makers often need information to be both scientifically sound and meaningful, timely, valid, and responsive to institutional needs. The key issue, then, is not only to gather more data but also to develop integrative frameworks that bring together data generation, analysis, interpretation, communication, and decision-making.

This review addresses this challenge by focusing on integrative approaches to environmental monitoring in the Anthropocene. The term "from data to decisions" emphasizes that monitoring the environment must be seen not as a step toward making a decision, but as a complete knowledge-action process. In this type of system, uncertainties are measured; stakeholders are involved; data is acquired and managed; data is analyzed and modeled; results are visualized; data is translated into policy; and the policy is adapted and managed. The conceptual flow from Anthropocene pressures through monitoring data, analytical integration, decision-support tools to adaptive governance is summarized in **Figure 1**, which shows the across-disciplinary logic of the article. The utility of monitoring is not just based on the accuracy of measurement instruments, but on whether information derived from monitoring can be used in early warning, in risk assessment, in restoration planning, in regulatory enforcement, in climate adaptation planning, in conservation prioritizing, and in sustainable development [11].

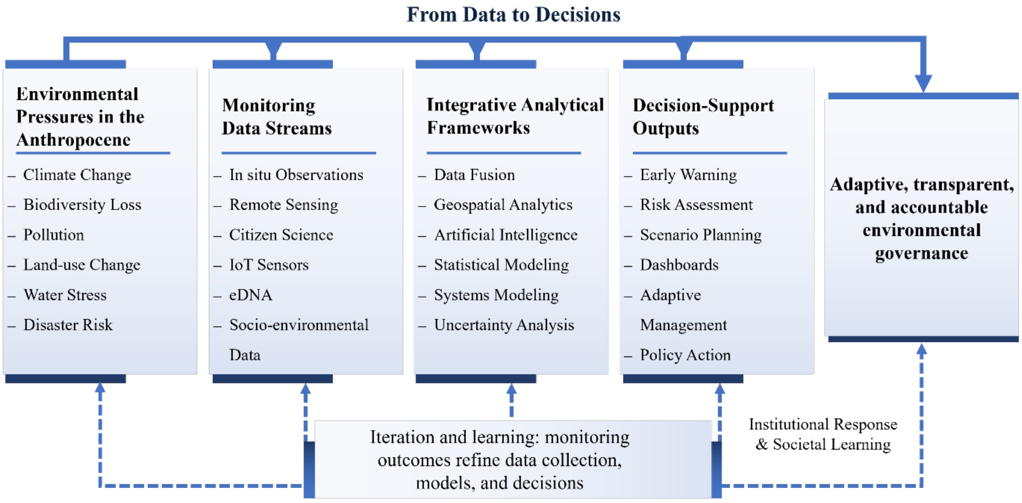

Figure 1. From data to decisions: a conceptual pathway for integrative environmental monitoring in the Anthropocene.

The novelty of the review here is that it focuses on synthesizing environmental monitoring as an integrated decision-support architecture rather than a set of discrete technologies or disciplinary practices. Most existing reviews focus on a single aspect, e.g., remote sensing applications, sensor networks, ecological indicators, machine-learning models, or citizen science programs. These contributions are important, but they do not necessarily address the systemic problem of integrating diverse data sources and using them to make decisions in an uncertain, complex world. To broaden this perspective, this article positions environmental monitoring at all stages of the pathway, from data production to decision-making, through to decision implementation [12]. It does so through the lens of the links between technical integration, analytical strength, governance significance, and social acceptability.

The second new novel feature is the focus on multi-source and multi-scale integration. Environmental issues related to the Anthropocene are seldom overcome by a single observation scale or data type [13]. For instance, they may need to use satellite-based habitat metrics, field species inventories, acoustic recordings, environmental DNA, climate data, land use records, and community observations all together to effectively monitor biodiversity [14]. Likewise, an urban environmental health assessment can combine air quality sensors, satellite thermal imagery, traffic information, demographic fragility metrics, and hospital data. The article highlights the integrative opportunities and demonstrates the potential of environmental monitoring to shift beyond the narrow indicators to a more holistic view of coupled human–environment systems.

A third is attention to the relevance of the decisions. Numerous monitoring programs provide useful scientific information, but are not tightly coupled with management cycles, regulatory processes, or policy windows. This review thus not only reviews the processes of data collection and analysis, but also how environmental data are translated into usable knowledge—via decision-support systems, dashboards, scenario tools, early-warning platforms, and adaptive management frameworks [15]. Special focus is on communicating uncertainty, visualizing complex information, and converting scientific information into practical options for stakeholders. This framing, which is focused on making decisions, is important as the demand for governance responses to the dynamic nature of the threats in the environment grows in its need for speed, transparency, and accountability.

A fourth aspect of novelty is related to incorporating technological innovation along with ethical, institutional and participative aspects. New technologies such as automated monitoring, artificial intelligence, and big data infrastructures give rise to several significant issues of access, equity, transparency, algorithmic bias, and data privacy [16]. If finely-grained data and analytical ability are still limited to well-resourced regions or institutions, environmental monitoring systems can exacerbate existing inequalities. In contrast, responsible design, participatory monitoring and open data platforms can help to empower the general public with environmental knowledge and deepen their sense of stewardship [17]. Inclusiveness, trust, and governance capacity, are therefore addressed here as integral parts of monitoring effectiveness and not as secondary social issues.

It is organized in a way that yields a thorough integration of the data-to-decision pathway. It begins with a discussion of the changing data basis for environmental monitoring, the in situ, remote sensing, citizen science and emerging digital data streams [18]. Second, it reviews analytical tools that help us to combine and analyze different sources of data, such as data fusion, geospatial analysis, artificial intelligence, systems modeling and indicator-based evaluation [19]. Third, it looks at how the outputs of the monitoring can inform decision support systems, how they can be translated into policy, how they can support risk governance and how they can support adaptive management [20]. Fourth, it examines some of the most important applications in the areas of climate adaptation, biodiversity conservation, pollution control, ecosystem restoration, urban sustainability and water–land management [21]. Lastly, it pinpoints challenges that need to be addressed in the future and the need for interoperability, uncertainty management, responsible AI, institutional coordination, open science, and equitable participation [22].

This article attempts to bridge these themes into an idea and a practical approach for future environmental monitoring. Monitoring under the Anthropocene requires new and more technologically sophisticated, integrated, transparent, adaptive and socially responsive monitoring systems [23]. To bridge the gap between data and decisions, science needs to be connected to science, observation systems to governance needs, and environmental information needs to be credible, accessible, and actionable. This shift is critical to help facilitate resilient ecosystems, informed policy and sustainable human futures in the face of rapid environmental change.

2. Data Foundations for Environmental Monitoring

The ability to monitor rapidly changing, interdependent, complex systems across multiple data streams is crucial for environmental monitoring in the Anthropocene. The quality of environmental decisions is directly influenced by the quality, relevance, scale, and interpretability of the data that underpin the decision-making. Today, however, the monitoring of air, water, soil, and species abundance is not restricted to individual measures. It increasingly demands the ability to combine physical, biological, chemical, social, and technological information to understand the dynamics of coupled human–environment systems. Data foundations constitute more than a technical starting point of monitoring: they determine what changes to the environment are visible, which are considered risks, and whose knowledge enters into decision-making processes [12].

2.1. In Situ Monitoring Networks

However, in situ monitoring remains an important part of environmental assessment, as it provides direct information on environmental conditions. High-accuracy data from meteorological stations, hydrological gauges, air-quality monitors, soil sampling sites, biodiversity plots, and marine buoys are collected in the field and are crucial for detecting long-term data trends and for cross-checking with other data sources [4]. These are important measurements because they incorporate local environmental variation and can give a detailed picture of ecological processes that might not be directly observed by remote platforms.

Despite these attributes, in situ networks can be spatially uneven and institutionally fragmented [24]. Observing stations are usually clustered in areas with better scientific capacity, while many areas where biodiversity is greatest, climate conditions are most vulnerable, or political power is most marginalized, are poorly represented. This uneven distribution can negatively affect the accuracy of environmental assessments and the reliability of global models. Furthermore, the majority of in situ programs are geared towards specific thematic areas, such as water management, air pollution control, and forest inventory, and may limit their applicability to integrated environmental analysis. The challenge lies not only in increasing monitoring but also in enhancing network coordination to ensure that local monitoring measurements contribute to broader interoperable knowledge systems.

2.2. Remote Sensing and Earth Observation

The potential of remote sensing to monitor the environment has been revolutionized by its ability to repeatedly observe large areas at multiple spatial and temporal resolutions. Satellite-based sensors, aerial photography, drones, radar systems, hyperspectral sensors, and other tools provide valuable information about land-cover change, vegetation health, surface temperature, ocean conditions, wildfire dynamics, urban expansion, and ecosystem disturbance [25]. The technologies are particularly significant in inaccessible areas and for detecting environmental change across national borders, where field-based data might be scarce or contradictory.

The power of remote sensing lies in its ability to provide information on space-time patterns and trends that would not otherwise be observed. Satellite-derived indicators can monitor deforestation, wetland loss, glacier retreat, algal blooms, and drought stress across entire landscapes or regions. But remote sensing also has its drawbacks and requires careful interpretation. Many of the products are indirect proxies, and their reliability depends on sensor resolution, atmospheric correction, classification algorithms, and ground validation. Analysis can be further complicated by clouds, mixed pixels, and spectral confusion. So, remote sensing should not be seen as a substitute for field observation, but as an additional layer that can be added to the in situ layer and which can be useful from a scientific and decision-making perspective [26].

2.3. Citizen Science and Participatory Monitoring

Participatory monitoring and Citizen science in environmental data production are gaining importance. These approaches can boost spatial scale and monitoring frequency, and incorporate local knowledge and place-based information that may not be represented in formal scientific networks by involving local communities, volunteers, Indigenous groups, and non-specialist observers. Citizen observations have made valuable contributions to biodiversity recording, invasive species detection, water-quality assessment, tracking plastic pollution, and urban environmental monitoring [9].

Participatory monitoring is not just a technical issue but also a social and political one. It can reinforce environmental consciousness, boost trust among the citizens, and facilitate more democratic knowledge production [27]. Local communities most exposed to environmental degradation are likely to have extensive knowledge of seasonal cycles, species behaviors, pollution events, and land-use pressures. Environmental evaluations can be more contextually relevant and socially valid if systematic knowledge is incorporated into monitoring frameworks.

However, there are questions about participatory data, such as observer bias, uneven sampling effort, and data quality [28]. These concerns are well-founded, but should not preclude the use of citizen-generated data. Rather, strong protocols, training, validation techniques, and clear metadata will help to enhance reliability. Whether participatory monitoring is employed simply as low-cost data collection or as a true part of decision-making is a key question. Citizen science can be extractive without feedback mechanisms and institutional recognition.

2.4. Emerging Digital and Biological Data Streams

New types of environmental data have emerged in recent years and are changing the ways systems are monitored. The Internet of Things sensor network can measure the air quality, water level, soil moisture, noise, temperature, and many other environmental variables [29]. The potential of environmental DNA for detecting invasive species, monitoring ecosystem health, and assessing biodiversity is immense; DNA from species in water, soil, or air can be detected [30]. Wildlife monitoring by bioacoustic sensors is possible by measuring soundscapes, and camera traps and automated image recognition enable continuous wildlife monitoring [31]. Indirect signals of environmental events, such as flooding, heat stress, and pollution incidents, can also be detected via mobile devices and social media.

The new data streams have unprecedented temporal resolution and sensitivity. They can detect short-term changes, unexpected occurrences, and subtle bio-indications that are not captured by traditional monitoring. They also create new data volume, calibration, standardization and data interpretation problems, however. The high-frequency sensors can generate large amounts of noisy data, whereas biological detection techniques, such as environmental DNA, face issues of contamination, transport, degradation, and false positives [32]. While automated systems may be more efficient, they can also distract from the ecological meaning of the technical output. The big question is ensuring that innovation generates knowledge about the environment, rather than just another data set. The key environmental data streams mentioned in this section are summarized in **Table 1**, which identifies their strengths, weaknesses, and applications in decision-making.

Table 1. Major data streams for environmental monitoring in the Anthropocene.

Data Stream	Typical Examples	Main Strengths	Key Limitations	Decision Relevance
In situ monitoring	Weather stations, hydrological gauges, soil plots, air-quality stations, ecological field surveys	High measurement accuracy; long-term trend detection; essential for validation	Spatially uneven; costly to maintain; often institutionally fragmented	Supports regulatory assessment, baseline monitoring, and model calibration
Remote sensing	Satellites, drones, aerial imagery, radar, hyperspectral sensors	Broad spatial coverage; repeat observations; useful for inaccessible regions	Requires ground validation; affected by resolution, cloud cover, and classification uncertainty	Enables land-use monitoring, disaster mapping, climate assessment, and conservation planning
Citizen science	Species observations, water-quality reporting, pollution mapping, local hazard reporting	Expands coverage; increases public engagement; captures local knowledge	Variable data quality; uneven participation; potential observer bias	Strengthens community-based monitoring and participatory governance
IoT and automated sensors	Low-cost air sensors, water-level sensors, acoustic sensors, smart buoys	Near-real-time data; high temporal resolution; early warning potential	Calibration problems; large noisy datasets; maintenance and power constraints	Supports rapid response, early warning, and continuous risk tracking
Biological monitoring innovations	Environmental DNA, bioacoustics, camera traps, automated image recognition	Detects hidden or rare species; improves biodiversity surveillance	Requires careful interpretation; risk of contamination or false detection	Supports biodiversity conservation, invasive species detection, and ecosystem assessment
Socio-environmental data	Demographic data, health records, land-use data, mobility data, social media signals	Links environmental hazards with exposure and vulnerability	Privacy concerns; ethical constraints; uneven availability	Supports environmental justice, risk assessment, and targeted interventions

2.5. Data Quality, Interoperability, and Standardization

Data quality is a crucial factor in the value of environmental monitoring. To be able to analyze with accuracy, precision, completeness, temporal consistency, spatial representativeness, and documentation of the metadata [33]. Across integrated monitoring systems, data quality becomes even more complicated as various data types are generated by different instruments, protocols, and resolutions, with varying assumptions. Harmonizing these datasets and combining them without proper harmonization can create misleading results, particularly if uncertainties are not considered or concealed.

Interoperability thus becomes a key attribute for transitioning from disjointed observations to connected environmental intelligence [34]. Standardized formats and common geospatial references, shared vocabularies, open metadata, and standardized quality-control systems facilitate inter-institutional and interdisciplinary comparison and combination of datasets. But standardization is not just a technical process. This also includes negotiation between scientific communities, the government, private actors, and local knowledge holders. Too much standardization can lose some contextual information, and too little can make synthesis difficult. Monitoring frameworks need to be comparable, but also sensitive to local ecological and social context.

2.6. Data Gaps, Biases, and Uncertainty

No environmental data are neutral depictions of reality. They represent decisions regarding spatial location(s) for monitoring, measures to be taken, technologies to be employed, and environmental values that are relevant [35]. Bias and data gaps can occur when research funding is unequal, geopolitical factors are at play, access is limited, monitoring priorities shift over time, and technology dependency is high. For instance, some geographic areas may be poorly sampled in global datasets, and some taxa may be sampled more heavily than others due to greater visibility. Landscapes in urban and economically productive locations are more likely to be well-known and developed than those in remote or out-of-the-way locations.

Uncertainty is an inherent aspect of environmental monitoring, and it's not a bad thing. A framed and shared uncertainty can enhance decision-making by specifying confidence levels, highlighting knowledge gaps, and avoiding overprecision. When uncertainty is overlooked, glossed over or hidden to produce more definite results, problems occur. The Anthropocene is characterized by dynamic, sometimes nonlinear, environmental systems, so monitoring frameworks need to embrace uncertainty as a key analytical tool [36]. That will involve statistical tools, but also institutional cultures that are willing to act in the absence of complete knowledge and are adaptive in the face of new evidence.

2.7. Ethical, Equity, and Governance Dimensions of Environmental Data

With a growing need for data in environmental monitoring, ethical and governance concerns gain visibility [12]. When communities, Indigenous territories, private land, or ecological resources are involved in the monitoring process, questions of data ownership, access, privacy, sovereignty, and benefit-sharing are particularly relevant. While open data can encourage transparency and scientific cooperation, there is also a risk that such data will be made available to others without the community's permission, leading to exploitation of these resources, particularly locations of endangered species.

Equity is a key issue in the creation of monitoring systems [37]. Frequently, technologically advanced sensor networks are located in wealthier areas, while the communities most vulnerable to environmental threats may have limited access to data or analytical skills. This can exacerbate environmental injustice, as the definition of risks and priorities may be done by some and not others, who are data-poor. Investing in capacity building, participatory governance, indicators that are locally relevant and understood, and multilingual communication are critical to more inclusive monitoring.

The technical sophistication of the data foundations for environmental monitoring is not the only criterion by which the data foundations can be judged; they must also be judged on their ability to inform credible, legitimate, and actionable decisions [12]. In the Anthropocene, improvements in monitoring don't just mean more sensors, bigger databases, or higher-resolution imagery. It involves creating an accurate, interoperable, transparent, socially responsible, and responsive data infrastructure for environmental management. Such foundations are the only ones that can allow the shift from isolated observations to cohesive decision-making.

3. Integrative Analytical Frameworks

Monitoring in the Anthropocene can be challenging and exciting due to an increasing number of environmental data streams. A more comprehensive understanding of change in the environment comes from large amounts of data from field networks, satellites, sensors, biological assays, and participatory platforms, but these data don't always get useful out of the gate. They vary in spatial resolution, temporal frequency, uncertainty, disciplinary origin, and institutional use. Integrative analytical frameworks are therefore crucial for the establishment of coherent knowledge from the heterogeneous observations. They are not just for data fusion, but they are also for discovering relations, identifying change, predicting threats, and informing decisions when confronted with uncertainty [12].

One of the key challenges is that integration is conceptual, institutional and technical. Analytical frameworks shape the ways environmental systems are represented, which variables are considered important, the nature of uncertainty and the types of decisions possible. Lack of careful design can make it seem as though the integration is thorough, but obscure bias, scale issues, or a lack of causal understanding. Reliable integrative frameworks, then, need to merge ecological thinking, clear assumptions, and decision-making interpretations with computational capability [3].

3.1. Data Fusion for Multi-Source Environmental Information

Data fusion involves merging data from various sources to create a more comprehensive and accurate picture of environmental conditions [18]. It can include combining satellite data with ground-based observations, sensor data with hydrological models, species data with habitat maps, and climate projections with socio-economic vulnerability information and more. The power of data fusion lies in its ability to overcome the shortcomings of single data sources. The benefits of remote sensing include extensive spatial coverage, but it may need to be field-validated; the benefits of in situ data include high accuracy, but limited spatial coverage; the benefits of citizen science include extensive spatial coverage, but it may require uneven sampling effort. If used judiciously, these sources can yield more robust evaluations than any one dataset could on its own.

But data fusion is not an easy aggregation task. There are data sets out there that measure similar but not identical data. For instance, a vegetation index derived from satellite data might suggest greenness, but not necessarily species diversity, ecosystem resilience, or habitat quality [38]. Similarly, air-quality sensors can detect changes in air quality in their immediate vicinity, but alone cannot account for population exposure without being combined with mobility, land-use, and population data. The analytical problem is: are datasets complementary, redundant, or possibly contradictory? Therefore, the procedures for calibration, validation, uncertainty propagation, and scaling up must also be incorporated into integrative frameworks.

A major risk in data fusion is the production of false precision. Several datasets can be combined into a single dataset, and the final product could appear authoritative even though the data may be highly uncertain [39]. This can be particularly challenging if fused products are applied in policy decisions, such as conservation prioritization, disaster response, and pollution enforcement. It is therefore imperative to have transparent documentation of the data provenance, model assumptions, and confidence intervals. Data fusion should aid understanding, not confusion.

3.2. Geospatial Analytics and Landscape-Level Assessment

Geospatial analytics offers a robust tool for analyzing environmental change. Patterns of land-use change, habitat fragmentation, watershed degradation, urban expansion, wildfire risk, and climate vulnerability can be studied using geographic information systems, spatial statistics, remote sensing analysis, and landscape modeling [40]. Geospatial methodologies are essential for linking observations to management units such as watersheds, protected areas, administrative units, and ecological corridors, since many environmental processes are spatially structured.

Geospatial analytics' strength is its ability to uncover spatial relationships that cannot be seen in non-spatial data [41]. Pollution exposure can be measured against road, industrial, population density, and socio-economic vulnerability, for example. Measures of biodiversity loss can include habitat connectivity, edge effects, and land-use intensification. The combined use of elevation, rainfall, soil saturation, drainage infrastructure, and settlement patterns can be used to assess flood risk. These analyses enable the transition from isolated measurements to spatialized decision support for environmental monitoring.

However, there are significant constraints on geospatial frameworks [41]. Interpretation may be greatly impacted by spatial resolution. Coarse-resolution datasets remove local heterogeneity, whereas high-resolution datasets can introduce excessive detail, which does not necessarily make them more useful for decision-making. A second ongoing challenge is scale mismatch, in which ecological processes may occur at the watershed or landscape scale, while policy action occurs at the administrative scale. Furthermore, spatial models can exacerbate social and geographical inequalities when data are imbalanced. The availability of mapping infrastructure can be reflected in a region's apparent importance in the environmental assessment, and the absence of mapping can be equated with a lack of importance.

These are only a few reasons why critical geospatial analysis goes beyond the production of maps. Maps are powerful statements but also selective representations. Classification uncertainty, spatial bias, temporal comparability, and the political implications of visualizing environmental risk are all aspects of responsible use. A map can inform effective action, but can also be a misguided interpretation of contested landscapes if local knowledge and governance context are overlooked [42].

3.3. Statistical Modeling and Environmental Inference

In the field of environmental monitoring, statistical modeling continues to play a key role as the means of estimating trends, testing relationships, identifying drivers, and quantifying uncertainty [43]. Researchers can use regression models, hierarchical models, Bayesian frameworks, time-series analysis, species distribution models, and spatial statistics to draw inferences from raw data. In long-term monitoring, statistical methods play a significant part in distinguishing real changes in the environment from sampling error, measurement error, or natural variation.

An important role of statistical modeling is to explicitly address uncertainty. Environmental data is frequently incomplete, noisy, and sparse. Statistical frameworks can enable the estimation of missing data points, address sampling bias, and provide confidence in observed results. Bayesian models are particularly useful when it is necessary to combine prior knowledge, expert judgment, and new data. Hierarchical models can incorporate information from across multiple sites, scales, or species, and are useful for ecological and climate assessments [44].

But statistical models are as good as their assumptions. Many environmental systems are nonlinear, dynamic, and driven by interacting drivers. Linear models, stationary models, or independent observation models may not hold in the case of rapid environmental change. Another hurdle is that the numbers may not be relevant to decision-making. For a trend to be useful to management, it needs to be large, timely, and sufficiently relevant. For a trend to be useful for management, it must be large, timely, and relevant. On the other hand, decisions may have to be made before the statistical certainty is reached. Hence, making environmental inferences is necessary but should be connected to management thresholds, risk tolerances, and adaptive decision-making [45].

3.4. Machine Learning and Artificial Intelligence

Because they can handle large, complex, and high-dimensional datasets, machine learning and artificial intelligence have emerged as powerful tools in environmental monitoring [7]. Applications include: land-cover classification, species identification, pollution forecasting, wildfire prediction, climate-impact modeling, anomaly detection, and automated interpretation of image, sound, and genetic data. They are useful in monitoring systems where there is a large amount of data and the patterns are not easily definable.

The most significant benefit of machine learning is its ability to make predictions. Satellite imagery can be classified, animals in camera-trap images can be identified, bird calls in acoustic recordings can be detected, and complex input data can be used to predict environmental variables using deep learning models. AI-based systems can facilitate near-real-time monitoring by enabling near-real-time data processing [46]. This is especially important for early warning systems because of the time lag that can impact the effectiveness of response to floods, fires, harmful algal blooms, or pollution events.

However, with the increased adoption of AI come important questions. Numerous machine-learning models are "black box" models that deliver predictions without any explanation. In Environmental Governance, opacity can contribute to a lack of trust and can make it hard to rationalize decisions [47]. Another restriction is the model's transferability. The algorithm developed in one ecological, climatic, or socio-economic environment might not work as well in other environments. However, if the training data is unequally represented, this can lead to biased model output, particularly if underrepresented regions, species, or communities are not included in the model-building process [48].

Another danger lies in technological complacency. Good predictive accuracy on a test set does not necessarily reflect causal mechanisms or the model's ability to remain accurate in the future under new environmental circumstances. Environmental systems can deviate from the range of historical training data in the Anthropocene, reducing model effectiveness [49]. Thus, AI can be employed within an interpretation framework comprising domain expertise, validation, uncertainty analysis, and ethics. More sophisticated algorithms are not the only ones that will shape the future of environmental AI; applications must be explainable, responsible, and context-sensitive.

3.5. Systems Thinking and Socio-Ecological Modeling

Rarely are environmental issues in the Anthropocene the consequence of only a single cause. The drivers of climate change, biodiversity loss, land degradation, water scarcity, and pollution result from interactions among ecological processes, economic systems, governance arrangements, technologies, and human behavior [2]. These interdependencies can be understood through a systems-thinking approach. Systems approaches focus on feedback loops, thresholds, trade-offs, cascading effects, and cross-scale interactions, rather than on the analysis of environmental variables individually.

This is because socio-ecological models acknowledge that environmental change cannot be separated from human decision-making. Ecological outcomes are shaped by land use change, resource extraction, conservation policy, agricultural practices, urban planning, and consumption patterns [50]. Integrated models can connect biophysical processes to economic rewards, institutional factors, and trends in population and social susceptibility. This makes them useful for scenario analysis, policy evaluation, and adaptive management.

The ability to see unintended consequences is the critical strength of systems thinking. For instance, a water policy aimed at boosting crop yields might promote more intensive water extraction, diminish habitat connectivity, and increase downstream pollution [51]. In the same way, failing to address broader market forces can cause forest conservation in one place to shift deforestation to another. Anticipation of trade-offs by decision-makers can occur when systems frameworks are used.

But there are challenges as well with socio-ecological modeling. The more complex the model, the more complicated it is to validate, communicate, and apply in policy settings. They may need vast quantities of data that are either unobtainable or questionable. Furthermore, incorporating social variables may be methodologically and politically awkward. However, cultural, institutional, and ethical aspects cannot be removed from human behavior and cannot be simplified without losing some of their nuance. Therefore, system models are designed as learning tools rather than as accurate representations of reality. Their utility could be in making assumptions explicit, considering scenarios, or facilitating conversations with stakeholders [52].

3.6. Indicator-Based Frameworks and Composite Indices

Indicators are used extensively in environmental monitoring because they make much of the environmental information measurable. Biodiversity, ecosystem health, water quality, air pollution, land degradation, climate vulnerability, and sustainability indicators enable decision-makers and researchers to monitor progress, compare regions, and report on the environment [53]. Multiple indicators can also be combined into composite indices that can aid reporting and policy assessment.

The attractiveness of indicator-based frameworks is found in their communicative potential. Oftentimes, decision-makers require short bits of information rather than a lot of raw data. Indicators are useful tools for translating complex environmental dynamics into easily understood measures when designed well. For instance, indicators of habitat connectivity, species abundance, carbon storage, or water stress could be used to prioritize interventions and assess management outcomes [54].

But there is also a process of simplification and value judgment in indicators. Choices of indicators define what is measured and what is not [55]. A biodiversity index can focus solely on the number of species and ignore other aspects, such as genetic diversity, ecological interactions, or cultural values. A sustainability index may combine environmental and socio-economic impacts, potentially in a distortionary way. The weighting scheme and normalization technique used are particularly critical for the composite indices, as are the data availability requirements. In the absence of transparency in these decisions, indicators can give a false sense of objectivity.

For a critical approach to indicators, one should ask the following questions: Is it scientifically valid? Is it policy-relevant? Is it sensitive to change? Is it understandable? Is it ethically appropriate? Indicators should not be selected just because data are available. They should reflect ecological processes and decision needs. Furthermore, indicator frameworks should be flexible, as the system's needs and dynamics evolve. Static indicators may be unable to detect emerging risks or transitions in the Anthropocene [56].

3.7. Uncertainty, Transparency, and Model Governance

From every analytical perspective on integration, uncertainty cannot be avoided. It can result from measurement error, sampling error, model structure, parameter estimation error, temporal variation, and lack of knowledge of environmental processes. Uncertainty may also stem from social, economic, and political issues in decision contexts. The question is not one of eradicating uncertainty but of representing it, and using it responsibly [57].

Transparent communication of uncertainty is crucial to credible environmental monitoring. Decision makers must be aware not just of what a model is predicting, but how sure they are of the prediction, what assumptions are behind it, and what the implications of a misprediction are. Other tools, such as scenario analysis, sensitivity testing, confidence intervals, ensemble modeling, and expert elicitation, can be used to communicate uncertainty more effectively [58]. But don't let uncertainty be an excuse not to act. Multiple environmental risks demand precautionary action without a full set of facts.

As analytical systems play a greater role in informing policy and management decisions, model governance is increasingly critical. Governance includes establishing standards for model validation, documentation, repeatability, accountability, and ethical application [59]. Open-source tools, workflows, and metadata can increase trust and enable independent evaluation. Meanwhile, data from the environment or communities can be sensitive and require restricted access and ethical protections. The issue is how to be open and responsible.

3.8. Toward Decision-Oriented Integration

Integrative analytical frameworks are not just about creating more advanced models, maps, or indices; they are about helping to make better environmental decisions [60]. This means delivering the results of the analysis to meet the users' needs. Monitoring systems need to be designed to align with time-to-decision, governance controls, risk thresholds, stakeholder values, and implementation capacity. A model that is technically sophisticated but not interpreted and acted upon may not be of much value.

Iterative learning is also required when integrating for decision-making [61]. Environmental monitoring shouldn't be a report or dashboard. The outputs from the analysis should be linked to management actions, and the results of those actions should be tracked to inform better decisions in the future. This results in a feedback loop of data, analysis, policy, and practice. In this regard, integrative frameworks are at the heart of adaptive management. In **Table 2**, a comparative synthesis of the main analytical frameworks, their integrative functions, limitations, and best-use contexts is provided.

Table 2. Integrative analytical frameworks for transforming environmental data into knowledge.

Analytical Framework	Core Function	Contribution to Integration	Critical Challenges	Best-Use Contexts
Data fusion	Combines multiple datasets into unified outputs	Links satellite, field, sensor, and social data across scales	Scale mismatch, uncertainty propagation, false precision	Multi-source environmental assessment, hazard mapping, ecosystem monitoring
Geospatial analytics	Analyzes environmental patterns across space	Connects environmental change to landscapes, watersheds, cities, and governance units	Spatial bias, resolution effects, and political interpretation of maps	Land-use change, habitat fragmentation, pollution exposure, and flood risk
Statistical modeling	Estimates trends, relationships, and uncertainty	Converts raw observations into inference and confidence estimates	Assumption sensitivity, nonlinearity, and limited stationarity under rapid change	Long-term trend analysis, species distribution, hydrological, and pollution modeling
Machine learning and AI	Detects patterns and predicts outcomes in complex datasets	Processes large-scale imagery, sensor, acoustic, and biological data	Opacity, bias, weak transferability, overfitting	Image classification, early warning, anomaly detection, and environmental forecasting
Socio-ecological modeling	Represents interactions between human and natural systems	Integrates ecological processes with governance, behavior, and vulnerability	Difficult validation; complex communication; social simplification risk	Scenario planning, adaptation policy, land-system governance
Indicator and index frameworks	Simplifies complex conditions into measurable metrics	Supports comparison, reporting, and policy communication	Indicator selection bias; weighting problems; oversimplification	Sustainability assessment, biodiversity reporting, ecosystem health monitoring
Uncertainty analysis	Quantifies and communicates confidence and risk	Makes limitations visible in integrated outputs	Often poorly communicated or ignored in policy contexts	Risk governance, precautionary decision-making, adaptive management

In the Anthropocene, the most valuable analytical systems will be those that combine scientific rigor with flexibility, transparency, and usability [62]. They must integrate multiple data sources without concealing uncertainty, apply advanced models without abandoning ecological understanding, and support decisions without oversimplifying social and environmental complexity. The transition from data to decisions, therefore, depends on analytical frameworks that are not only computationally powerful but also critically designed, ethically governed, and responsive to real-world environmental challenges.

4. Decision-Support Systems and Policy Translation

The usefulness of environmental monitoring is defined by its ability to provide information to guide decision-making. Environmental risks in the Anthropocene are dynamic, interconnected, and, in some cases, irreversible, and monitoring systems need to shift from passively monitoring the environment to making decisions about it. Scientific knowledge and science models can enhance scientific understanding, but they do not necessarily lead to better governance. Institutional pathways, interpretive tools, stakeholder engagement, and uncertainty management are needed to translate monitoring outcomes into policy actions. Decision-support systems thus serve as a pivotal link between data and decisions: they transform data, information, and knowledge into actionable information to inform planning, regulation, emergency responses, conservation, restoration, and adaptation [15].

But decision support is not solely about science/policy interaction through a technical interface. It also has a social and political character shaped by values, priorities, institutional capacities, and power relations. There are often competing goals in environmental decision-making, including economic development, biodiversity protection, public health and safety, climate resilience, and social equity. In fact, despite the usefulness of monitoring evidence in clarifying risk and trade-offs, it usually doesn't stop conflict. A critical approach to decision support, therefore, should not only address the issue of information generation but also the mode of information interpretation, confidence in information, mode of communication, and action on information [63].

4.1. Bridging Environmental Monitoring and Governance

Information is the basis of environmental governance, and it has to be credible and timely [64]. Pollution monitoring information can be used to determine whether pollution levels are being exceeded, whether protected areas are functioning, whether ecosystems are being degraded, whether climate risks are increasing, or whether restoration efforts are effective. A recurring challenge is the lack of linkages between monitoring programs and governance processes. Many monitoring systems are based on scientific goals rather than on a particular decision-making need. Consequently, they may generate good data that come too late, are not policy-relevant, and/or are not at the spatial and temporal scales of decision-making.

However, bridging this gap needs a decision-oriented monitoring design. This includes: defining from the start the decisions the monitoring system will inform and who will use the information; identifying thresholds or indicators that will be relevant; and specifying the management actions to be taken when evidence is gathered. A water-quality monitoring system, for instance, should include not only pollutant concentration information but also link concentrations to regulatory standards, public health advisory information, enforcement tools, and remediation plans. Likewise, conservation goals, land-use plans, habitat restoration priorities, and adaptive management cycles should be linked to biodiversity monitoring [65].

The challenge is to match the complexity of science with institutional decision-making. Governance systems tend to be simpler, which is important for a range of short deadlines, defensible evidence, and categories; environmental systems are more uncertain, nonlinear, and context-dependent. This imbalance can result in either under- or oversimplification of science or the underuse of evidence. Therefore, effective decision-support frameworks must be a compromise between scientific rigor and administrative practicality, yet maintain ecological meaning and transparency [66].

4.2. Decision-Support Systems for Risk Assessment and Early Warning

DSSs are particularly useful in situations where environmental hazards arise quickly, or if they are not acted upon in a timely fashion, they can have far-reaching consequences. Combined monitoring data, predictive models, and automated alerts are increasingly used in early-warning platforms for floods, droughts, wildfires, heatwaves, hazardous pollutants, disease vectors, and harmful algal blooms [67]. These systems can enhance preparedness by transforming environmental signals into comprehensible, community-actionable warnings for authorities and communities.

Early Warning Systems are powerful because they help to reduce the time lag between detection and response. Information from sensors, satellites, weather models, and field reports can provide near-real-time data and help identify potential hazards before they become severe [68]. But the accuracy of the predictions is not the only condition of early warning. Even if it is technically correct, a warning can fail when it is not clearly communicated, is not trusted by recipients, and/or is not linked to response capacity. On the other hand, there is a risk of warning fatigue and the loss of public confidence if there are too many false alarms.

Exposure and vulnerability need to be considered in the risk assessment process. Not all communities are impacted by environmental hazards in the same way. The danger of a heatwave, flood, or air pollution event increases when it combines with poor infrastructure, poverty, health and vulnerability, limited mobility, and weak public services. Hence, decision support systems need to incorporate the biophysical hazard data with demographic, socio-economic, and infrastructural data[15]. This integration is expected to contribute to the transition from hazard-based to vulnerability-oriented risk assessment. If not, monitoring systems can determine where environmental threats are present, but not who is at risk.

4.3. Scenario Planning and Adaptive Management

Scenario planning is a key decision-support approach for managing uncertainty. Rather than predicting a single future, scenario tools explore multiple plausible futures under different assumptions about climate change, land use, policy interventions, population growth, technological development, or economic activity[69]. This is particularly important in the Anthropocene, where historical trends may no longer provide reliable guidance for future conditions. Scenario-based decision support enables managers and policymakers to assess the robustness of strategies under uncertain futures.

For example, climate adaptation planning may use scenarios to compare the consequences of different emissions pathways, urban growth patterns, water-demand trajectories, or ecosystem restoration strategies[70]. Conservation planning may examine how species distributions could shift under alternative climate and land-use futures. Disaster-risk management may evaluate how infrastructure investments perform under varying flood or wildfire scenarios. The value of such tools lies not in producing exact forecasts, but in helping decision-makers understand trade-offs, vulnerabilities, and options.

Adaptive management complements scenario planning by treating environmental policy as an iterative learning process[71]. In adaptive management, decisions are implemented, outcomes are monitored, and strategies are adjusted based on evidence. This approach is well-suited to uncertain and changing systems because it acknowledges that knowledge is incomplete and that management actions themselves can generate learning. However, adaptive management is often difficult to implement in practice. Institutions may lack flexibility, funding cycles may favor short-term outputs, and political pressures may discourage acknowledgment of uncertainty or failure. For adaptive management to work, monitoring must be embedded within governance systems that are willing to revise decisions as conditions change.

4.4. Visualization, Dashboards, and Digital Platforms

Visualization tools and digital dashboards are now well-established means of making environmental information readily available. Maps, graphs, risk indices, interactive platforms, and digital twins can assist in exploring environmental conditions, comparing conditions across scenarios, and tracking indicators over time[72]. A well-designed visual interface can communicate complex data to decision-makers who, for many reasons, may not be technically savvy. They can also help bring transparency by giving stakeholders a view of the evidence underpinning policy decisions.

However, it is important to note that visualization is not an objective process. Dashboard design affects perceptions of risk, priority, and uncertainty[73]. Interpretation may be affected by color schemes, classification thresholds, spatial boundaries, and aggregation methods. Although it may seem objective to have a map of "high-risk" areas, such maps can be based on hazard probability, exposure, vulnerability, and an acceptable level of risk. Likewise, the indicators showcased on dashboards might mask variation within communities or ecosystems.

An important issue with using dashboards is that they can give the illusion of control[73]. With the aid of real-time visualizations, it might seem that environmental systems can be fully observable and fully manageable, despite considerable uncertainties. Digital twins and interactive platforms can enhance scenario exploration, but can also be misleading and overly sophisticated if they don't incorporate scientific accuracy. Thus, metadata, uncertainty ranges, method explanations, and connections to decision contexts should be part of the visualization tools. Their job should be to assist in making informed judgments, rather than to make judgments for them.

4.5. Science–Policy Interfaces and Knowledge Translation

The science–policy interface is the boundary between science and policy and serves as the institutional and communicative environment for interpreting environmental evidence for governance[74]. Knowledge translation is more than just the dissemination of scientific knowledge. It's a conversation among researchers, policymakers, practitioners, communities, and other actors. Evidence, timelines, uncertainty, and legitimacy may differ for each group. Scientists can focus on methodological rigor, while policymakers need to know how to act as soon as possible and in a legally sound way. Communities may look for lived experience, community impacts, and procedural fairness.

These differences can be addressed through boundary organization, advisory panels, technical working groups, and participatory assessment processes [75]. They can take scientific results and make them accessible for policy decisions, identify what information is needed, and ensure that decision-makers understand the boundaries of the available scientific information. Science–policy interfaces are, however, prone to politicization, the use of selective evidence, and institutional inertia. Environmental data can be disregarded when it conflicts with economic interests or political priorities. Scientific information, on the other hand, can be used symbolically to validate decisions already made.

Knowledge translation has to be transparent and reflexive, therefore. It should explain what is known and unknown, the assumptions being made, and the trade-offs being considered. Translation is not simplifying messages, in the sense of the word, but resolving uncertainty. Instead, it involves expressing uncertainty in a way that enables responsible action. In many environmental situations, the time it takes to obtain a full diagnosis can cause permanent damage. Decision-support systems must thus allow for both precautionary and adaptive action and must not compromise science [76].

4.6. Regulatory Integration and Institutional Capacity

If monitoring is to have an impact on the environment, it must be linked to regulatory and institutional frameworks. Environmental impact assessment, compliance monitoring, pollution control, management of protected areas, land-use zoning, climate adaptation planning, and restoration evaluation are all areas where data can be used to support these efforts [77]. But regulatory integration can be limited by the rigidity of existing laws, inadequate enforcement resources, unclear agency jurisdictions, and incomplete data.

A problem is that regulation might be based on a single-pollutant threshold, whereas current environmental issues require a multi-stressor approach that accounts for cumulative effects. For instance, a particular ecosystem can have moderate nutrient pollution, moderate warming, moderate habitat fragmentation, and moderate pressure from invasive species. Still, together they can cause severe degradation, even though each factor is below a regulatory limit. Institutions need to shift away from individual compliance measures, however, and toward more cumulative and systems-based measures; decision-support systems must facilitate that shift [63].

The capacity of institutions is also critical. The best system in the world is of little use if agencies lack the staff, resources, knowledge, or legal authority to use the data they collect to take action. Governance with a lot of data and little capacity can lead to frustration and inaction. Investment in technology, however, is not enough to create robust decision-support systems; training, interagency coordination, data governance, and long-term maintenance are also required. Routine use and institutional ownership are essential for the sustainability of decision support, rather than innovation driven by projects [20].

4.7. Stakeholder Engagement, Legitimacy, and Trust

The decisions made regarding the environment impact a wide range of stakeholders: governments, industry, local communities, Indigenous peoples, landowners, scientists, and civil society groups [78]. A decision-support system that omits affected groups, even if it is technically sound, is not necessarily legitimate. Engaging with stakeholders can enhance the relevance of monitoring indicators, bring local risks to light, make local barriers more apparent, and help build trust in environmental information.

Trust is particularly relevant when they have to make decisions that involve limitations or compromises, or an unequal burden [78]. For example, if there is a sense of bias, opacity in monitoring data, or if monitoring data is imposed from outside, land-use controls, water allocation rules, pollution penalties, or conservation zoning can lead to resistance. Involving stakeholders in determining the questions to be posed, interpreting the results, and evaluating management options can be part of the solution. But participation needs to be substantive and not symbolic. Consultation, if limited to consultations once decisions have already been made, may further undermine trust rather than foster legitimacy and acceptance.

Power imbalance is a critical question. Not all stakeholders have the same influence over decision-making. The use of technical language, digital platforms, and data ownership may advantage specialist and institutional actors and disadvantage less formally empowered community actors. Decision-support systems must thus be made accessible, linguistically appropriate, culturally contextual, and procedurally just[7]. Environmental intelligence is more actionable if it is also socially legitimate.

4.8. From Information Products to Decision Pathways

One recurring problem in environmental monitoring systems is the belief that generating information is enough. Reports, maps, indicators, and dashboards are usually seen as finished products, but they are only steps on the way to the finished product. The question here is how these products enter decision pathways. Who is the recipient of the information? What power do they have? Which action does this activate? What is the measurement of outcomes? If there are no pathways, monitoring can create knowledge in the absence of change[72]. **Table 3** highlights the nature of key decision-support tools and the types of monitoring outputs that can support early warning, risk mapping, scenario planning, dashboards, digital twins, and adaptive management.

There needs to be clear connections between evidence, responsibility, action, and feedback along decision pathways[79]. For example, water-use restrictions, agricultural advisories, reservoir management, and vulnerable communities should be linked to early drought warnings. A biodiversity decline indicator should be related to habitat protection, restoration funding, land-use regulation, or species recovery planning. A pollution exceedance should link to enforcement, notification, and remediation. The linkages need to be planned for a crisis, since constructing decision pathways during an environmental crisis is time-consuming.

Table 3. Decision-support tools linking monitoring outputs to policy and management.

Decision-Support Tool	Primary Purpose	Required Data Inputs	Strengths	Critical Risks	Example Decisions Supported
Early-warning systems	Detect and communicate emerging hazards	Sensor data, satellite observations, weather forecasts, risk thresholds	Enables timely response; reduces disaster losses	False alarms, warning fatigue, weak community reach	Flood evacuation, wildfire alerts, heat-health warnings
Risk maps	Identify spatial patterns of hazard, exposure, and vulnerability	Geospatial hazard data, demographic data, and infrastructure layers	Supports prioritization and resource allocation	Can obscure uncertainty or reinforce spatial inequities	Zoning, emergency planning, and infrastructure protection
Scenario tools	Explore alternative futures and policy options	Climate projections, land-use models, socio-economic pathways	Helps manage uncertainty and compare strategies	Results may be misread as predictions	Climate adaptation, water planning, and conservation strategy
Environmental dashboards	Present indicators and trends in accessible formats	Real-time or periodic monitoring data, model outputs, metadata	Improves transparency and communication	Oversimplification; illusion of control	Pollution reporting, ecosystem status tracking, urban sustainability
Digital twins	Simulate environmental systems and management interventions	High-resolution spatial data, sensor feeds, process models	Supports interactive planning and system-level analysis	High cost; model opacity; data dependency	Smart-city planning, watershed management, coastal resilience
Adaptive management platforms	Link monitoring, action, evaluation, and learning	Baseline data, intervention records, outcome indicators	Closes the feedback loop between science and management	Requires institutional flexibility and long-term commitment	Restoration evaluation, protected-area management, water allocation

The central theme is that DSS should not be just info-givers but environmental governance infrastructures[20]. They must be effective in terms of analytical quality, institutional alignment, stakeholder trust, and adaptive feedback. The most useful systems in the Anthropocene, a context characterized by fast and unpredictable change, will be systems that leverage monitoring to inform timely, transparent, and accountable action. The shift from data to decisions, then, will require not only better information but also better decision architectures that can learn, respond, and govern amid uncertainty.

5. Applications, Challenges, and Future Directions

The usefulness of integrative environmental monitoring becomes apparent when it is applied to practical problems. The Anthropocene is a period in which environmental change does not occur in isolation; climate instability, biodiversity loss, pollution, land degradation, water stress, and public health risks all interact, making diagnosis and response difficult[2]. Rather than the sophistication of the data stream or the analytical model, monitoring systems should be judged by their ability to enhance decision-making across a variety of environmental situations. The focus of this section is on key application areas, and critical to the analysis are the ongoing challenges to moving from an abundance of information to effective governance.

5.1. Climate Change Monitoring and Adaptation Planning

One of the most critical and relevant fields for integrative environmental monitoring is climate change. There are a variety of climate indicators that provide key information on the dynamics of climate change, including temperature records, precipitation trends, glacier mass balance, sea-level rise, ocean heat content, vegetation changes, extreme-event frequency, and greenhouse gas concentrations[80]. However, when coupled with adaptation planning, climate monitoring can be especially helpful. There is a need for information beyond long-term climatic trends for communities, cities, agricultural systems, water managers, and conservation agencies, including near-term risks, vulnerability hotspots, and potential adaptation responses.

Climate observations and hydrological modeling, land use information, infrastructure mapping, demographic vulnerability indicators, and economic exposure estimates can all be linked to integrative frameworks[81]. This integration can help decision-makers identify the areas most vulnerable to extreme weather events, such as heatwaves, floods, droughts, fires, and coastal hazards. The need of the hour is the global and local nature of climate risks. While adaptation decisions may be made at the municipal, watershed, farm, or household level, global models are essential for projections. Downscaling and local validation are also required, but there will be uncertainty.

Another constraint is that while monitoring adaptation is often done in the physical domain, it may ignore social capacity[48]. It is possible that a technically accurate flood-risk map does not account for variation in evacuation access, insurance coverage, political representation, or public health vulnerability. This means moving from hazard mapping to vulnerability assessment is a necessary component of effective climate monitoring. There is a need to integrate climate signals with social conditions and communicate uncertainty clearly enough to enable timely action in climate decision support.

5.2. Biodiversity Conservation and Ecosystem Restoration

Due to species loss, fragmentation, invasive species, and ecosystem degradation, biodiversity monitoring has become increasingly urgent[21]. So traditional biodiversity surveys are important, but they remain slow, costly, and geographically constrained, limiting their ability to capture rapid changes in biodiversity. Integrative monitoring will enhance conservation efforts by synthesizing field inventories, remote sensing, environmental DNA, acoustic sensors, camera traps, citizen monitoring, and ecological models. Taken together, these data sources can provide a more detailed understanding of species distribution and ecosystem integrity.

Integrated monitoring can detect whether protected areas are helping to keep habitats connected, reducing deforestation, recovering species, or becoming isolated in the face of climate change, for protected area management[65]. Monitoring can help determine if interventions are leading to true restoration or merely to greening in restoration ecology. For instance, an increase in vegetation cover doesn't necessarily mean that biodiversity improves, because species composition, soil function, hydrology, or trophic interactions may still be degraded.

The problem is that biodiversity is not easily quantified. Ecosystem condition may be assessed using various measures, such as species richness and abundance, functional diversity, genetic diversity, ecosystem interactions, or cultural values. A monitoring program based on easily measured parameters can miss out on less obvious but ecologically important changes. In addition, conservation monitoring may be biased towards charismatic species or well-researched areas. Biodiversity monitoring in the future must therefore focus on ecological significance, the diversity of taxa, and local interest, rather than be limited to data availability or technological novelty [14].

5.3. Pollution Tracking, Environmental Health, and Urban Sustainability

Pollution monitoring highlights the need for environmental and human health information to be linked together. Ecosystems and communities are subjected to complex pathways of exposure to air pollutants, heavy metals, pesticides, plastics, nutrient runoff, industrial chemicals, and emerging contaminants [82]. Traditional pollution monitoring can be performed via fixed stations or periodic sampling, potentially missing short pulses, local hotspots, or non-uniform exposure. Assessment of environmental risk can be improved through integrative systems that use low-cost sensors, satellite observations, laboratory analyses, mobility data, land-use information, and data from health authorities.

Urban areas are particularly relevant because they are characterized by population, infrastructure, emissions, heat stress, waste generation, and social inequality. Urban air quality, urban heat islands, stormwater flows, noise, green space, and public health outcomes can be monitored to promote more sustainable planning [83]. But there is also an ethical question regarding urban monitoring when environmental data is associated with mobility, health, or demographic data. There must be a balance between seeking high-resolution exposure assessment and protecting privacy and community consent.

An important point to note is that pollution is not just a technical measurement issue; it is also an environmental justice issue. Exposure to pollution may become more widespread, and severe exposure may still be occurring among sensitive populations. To identify distributional inequalities, decision-support systems must go beyond the citywide or national level. Pollution monitoring should incorporate environmental chemistry, epidemiology, social vulnerability, and regulatory enforcement to maximize the potential of data to inform pollution prevention, accountability, and remediation in the future [83].

5.4. Water, Food, and Land-System Monitoring

There is a strong interdependency among water, food, and land systems that is increasingly under stress due to climate change, population growth, agricultural intensification, urban expansion, and ecosystem degradation [51]. To measure water quantity and quality, data on water level, water discharge, precipitation, groundwater level, reservoir storage, soil moisture, land cover, irrigation demand, and water sources of pollution should be integrated with data on ecological water needs. Likewise, crop conditions, soil health, pest infestations, fertilizer application, water availability, food systems, and climate extremes are all important factors to consider when monitoring food systems.

It is particularly beneficial for monitoring crop production and crop stress, deforestation, soil moisture, and land-use change, and this is especially true when done remotely [40]. The indicators derived from satellites, however, should be treated with caution, as productivity does not necessarily reflect sustainability. Groundwater extraction, nutrient pollution, degradation, and biodiversity loss may be linked to high yields. Integrated monitoring should therefore be based on trade-offs rather than on optimizing single outcomes.

Land-system monitoring also reveals the political nature of land data. Property rights, markets, food security, conservation, and development pressures are all influencing land use [84]. Monitoring can uncover deforestation, wetland conversion, illegal mining, or agricultural expansion, but whether this information triggers action depends on governance capacity and political will. There is a need to increasingly focus on the cumulative impacts of land change, supply-chain accountability, and social impacts in future land-system monitoring.

5.5. Disaster Risk Reduction and Early Response

Environmental Monitoring plays an increasingly important role in disaster risk reduction. Detection and response to floods, wildfires, storms, landslides, droughts, heat waves, and disease outbreaks are all time-sensitive [67]. Integrated early-warning systems can integrate meteorological predictions, satellite observations, hydrological models, sensor networks, social media signals, infrastructure data, and vulnerability maps. Such systems can enable officials to forecast risks and minimize losses.

But being effective at disaster monitoring requires more than prediction. Many disasters turn into catastrophes because warnings are not getting to vulnerable populations, response systems are not adequately resourced, or institutional responsibilities are not clear. For instance, a flood warning can't do any good if communities don't know about it, trust it, or have the ability to take action. Consequently, monitoring needs to be part of preparedness planning, public communication, evacuation arrangements, and post-event learning [85].

A major glaring omission is the preoccupation with short-term events and the lack of consideration for slow-onset disasters, including drought, desertification, groundwater depletion, and ecosystem collapse. These processes tend to be slow and may not raise immediate political issues. Therefore, a combination of fast-onset hazards and slow-moving risks should be monitored through integration. Anticipatory governance—rather than emergency governance—should be supported in future systems [86].

5.6. Persistent Technical and Institutional Challenges

While significant progress has been made, integrative monitoring remains hampered by technical issues. One of the primary issues is still data fragmentation [12]. Data is collected by different agencies, research groups, companies, and communities, with incompatible formats, standards, and access rules. This restricts synthesis and decision-making. There are also imbalances in data collection, such as limited monitoring in biodiversity hotspots, remote and inaccessible environments, and low-income areas. Consequently, global estimates might be the least reliable in areas with the highest environmental risks.

Analytical problems are also very critical. To combine multi-source data, one must address scale alignment, uncertainty propagation, validation, and careful interpretation. More sophisticated models can be accurate in specific areas or conditions and not in others, or at different times. As AI becomes more prevalent, questions about explainability, bias, reproducibility, and accountability come to the fore. Algorithmic systems can generate results that are hard to counterattack, even when they are central to important decisions, without clear governance [16].

The institutional challenges can be harder to overcome than the technical ones. Environmental change takes a long time to be observed, and monitoring systems are often funded for only a short period. Agencies may not have the resources to operate platforms, to understand complex outputs, or to act on evidence. A lack of integrated responses can result from sectoral fragmentation. Addressing these barriers will involve stable investment, interagency coordination, common standards, and institutional cultures that embrace learning and adaptation [24].

5.7. Equity, Participation, and Environmental Justice

Equity is a topic that needs to be addressed more directly in environmental monitoring going forward. Inequalities can be exacerbated by technological innovations that keep high-level monitoring systems in the hands of better-resourced institutions. At the same time, poor communities lack access to monitoring data, data interpretation, or decision-making power. Data-rich governance can be unfair if those impacted are not part of the decision-making processes for setting up priorities for monitoring and for making sense of results [16].

Participatory monitoring is one way to create more equitable systems, but participation needs to be meaningful. Communities should not be a source of data for outside experts, but should be involved in the research questions, indicators, interpretation, and management response. The significance of indigenous and local knowledge is particularly pronounced in the context of these systems, which often have long-term, place-based knowledge of environmental changes. However, incorporating such knowledge must take into account intellectual sovereignty, consent, and benefit-sharing [27].

Environmental justice also calls for monitoring systems to uncover inequities in exposure, vulnerability, and access to environmental benefits [37]. This involves identifying communities that are disproportionately impacted by pollution, climate risks, degraded ecosystems, or a lack of green infrastructure. Future monitoring systems should thus incorporate the dimension of justice as an essential part of their assessment, and not treat it as an option.

5.8. Future Directions for Integrated Monitoring

New environmental monitoring systems need to be interoperable, adaptive, transparent, and decision-oriented. Open science and shared data infrastructures can facilitate collaboration, but must not come at the expense of protecting sensitive ecological, community, and Indigenous data. AI can be used to improve pattern recognition and prediction, but it needs to be explainable, validated, and accountable. Digital twins and real-time dashboards can help enhance scenario planning, but they should not be used to create a false sense of security, nor should they take the place of stakeholder debate [7].

A significant future course is the creation of monitoring systems that close the loop between observation and action. Data should lead to decisions, decisions to outcomes, and outcomes for monitoring and improving future strategies [87]. This demands connecting monitoring with adaptive management, regulatory processes, and community-based governance. There needs to be a transition from creating information products to creating learning systems. The strategic priorities for future environmental monitoring are summarised in **Figure 2,** which highlights that environmental monitoring must be technologically innovative, analytically transparent, integrated into governance processes, and socially legitimate. **Table 4** summarizes the key themes across the sectors regarding application areas, monitoring priorities, integration requirements, barriers to integration, and future directions for environmental monitoring in the Anthropocene.

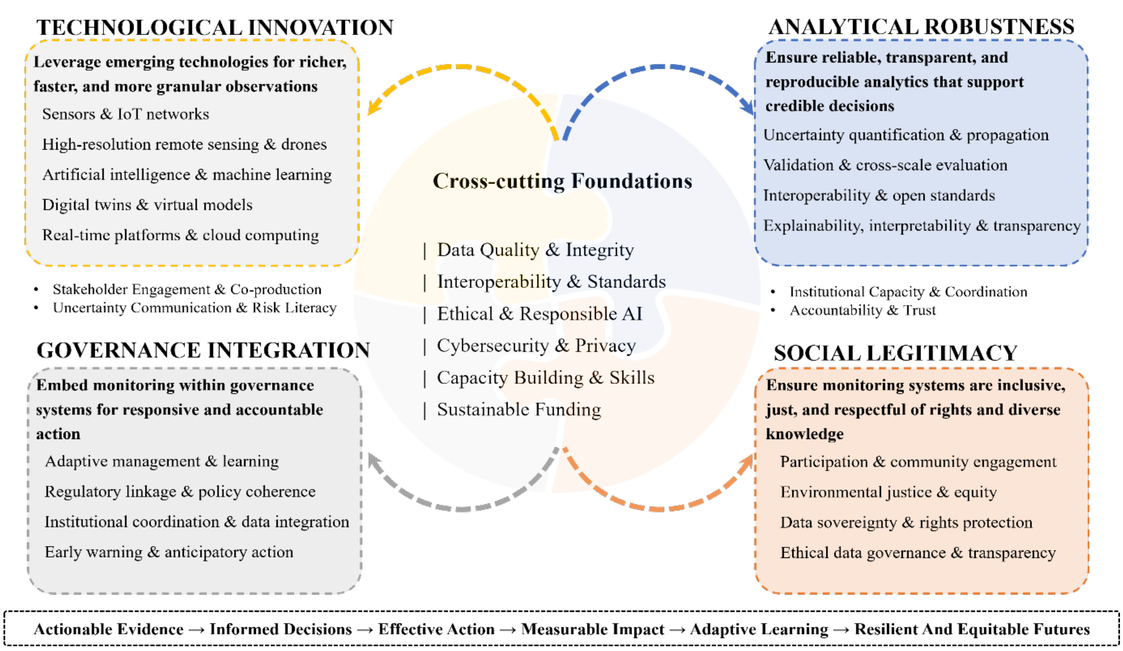

Figure 2. Strategic roadmap for integrated environmental monitoring in the Anthropocene.

Table 4. Applications, barriers, and future directions for integrative environmental monitoring.

Application Area	Monitoring Priorities	Main Integration Needs	Persistent Barriers	Future Direction
Climate adaptation	Heatwaves, droughts, floods, sea-level rise, wildfire risk	Climate observations, projections, infrastructure, vulnerability data	Downscaling uncertainty; weak local capacity; social vulnerability gaps	Place-based climate services and adaptive risk governance
Biodiversity conservation	Species trends, habitat condition, ecological connectivity, and invasive species	Field surveys, remote sensing, eDNA, acoustic data, citizen observations	Taxonomic bias, under-monitoring of remote regions, and simplified indicators	Multi-taxa, multi-scale biodiversity intelligence systems
Pollution and environmental health	Air, water, soil, chemical exposure, waste, and emerging contaminants	Sensors, laboratory analysis, health data, demographic vulnerability	Unequal monitoring coverage, privacy concerns, and weak enforcement	Justice-oriented exposure monitoring and accountability systems
Urban sustainability	Heat islands, air quality, green space, stormwater, noise, mobility	Sensor networks, satellite data, planning data, public health records	Data privacy; fragmented urban governance; unequal service access	Integrated urban environmental dashboards with equity metrics

Table 4. *Cont.*

Application Area	Monitoring Priorities	Main Integration Needs	Persistent Barriers	Future Direction
Water and land systems	Water quantity, water quality, soil health, land-use change, food production	Hydrological data, crop data, remote sensing, groundwater records	Competing sectoral demands; hidden cumulative impacts	Nexus-based monitoring of water–food–land trade-offs
Disaster risk reduction	Floods, fires, storms, landslides, droughts, slow-onset hazards	Hazard models, real-time monitoring, infrastructure, and vulnerability data	Warning: communication failures, weak preparedness, short-term focus	Anticipatory monitoring linked to response capacity
Ecosystem restoration	Vegetation recovery, biodiversity return, soil, and hydrological function	Baseline surveys, remote sensing, ecological indicators, and local knowledge	Superficial success metrics; short monitoring duration	Long-term adaptive restoration monitoring
Environmental justice	Unequal exposure, vulnerability, and access to ecosystem benefits	Environmental data, socio-economic data, and community knowledge	Power asymmetry, data ownership concerns, and lack of participation	Participatory and rights-based monitoring frameworks

Ultimately, the applications and challenges reviewed here show that environmental monitoring in the Anthropocene must be judged by its contribution to resilience, sustainability, and justice. The most effective systems will not necessarily be those with the largest datasets or most complex models. Still, those that generate credible evidence, communicate uncertainty, support timely action, and remain accountable to the societies and ecosystems they are intended to serve [66].

6. Conclusion

Environmental monitoring for the Anthropocene should be seen as more than just the recording of environmental observations. It continues to be a knowledge-action system, increasingly linking data with interpretation, governance, and societal response. Environmental issues are increasingly correlated, unpredictable, and inequitable as climate change, biodiversity loss, pollution, land degradation, water stress, and disaster risks increase. In this context, non-integrated, non-synchronized, or late monitoring systems are not enough. Transforming data to make sense of the vast amounts of information available, often unreliable and collected from a variety of sources, is now a central challenge.

This review has highlighted that the basis for environmental monitoring is constantly evolving. Conventional in situ networks still play a vital role in providing measurements. Still, they are now supported by remote sensing, automated sensors, citizen science, environmental DNA, bioacoustics, mobile technologies, and digital platforms. While these data streams provide unparalleled insights into environmental change at multiple scales, they also pose challenges related to interoperability, uncertainty, bias, and access. Too much information does not lead to greater understanding. If not carefully validated, interpreted, and properly governed, data abundance can lead to confusion, false precision, or misplaced confidence.

Therefore, integrative analytical frameworks are essential. To translate the multi-faceted observations into environmental knowledge, data fusion, geospatial analysis, statistical modeling, Artificial Intelligence, socio-ecological modeling, and indicator-based assessment may be helpful. However, these tools are not to be used without careful thought. Models and indices are representations of the real world, and their results are affected by assumptions, data availability, scale choice, and institutional priorities. Advanced analytics shouldn't be seen as a neutral or standalone tool. They are useful insofar as they are transparent, communicate uncertainty, have ecological understanding, can be reproduced, and meet actual decision requirements.

Decision Support Systems and Policy translation are crucial to the transition from monitoring to action. Decision-makers can use dashboards, early-warning systems, digital twins, risk maps, scenario tools, and adaptive management platforms to understand information better and act accordingly. However, without a clear decision pathway, these systems are only helpful if they can be implemented. Information should be accompanied by responsibility, authority, capacity to respond, and feedback. A warning that's missing from the vulnerable community; an indicator of biodiversity that doesn't impact land use; a pollution map that doesn't trigger enforcement; these are only partial forms of environmental intelligence.

One of the key learnings from this review is that the governance, ethics, and justice of environmental monitoring are part of the picture, too. The development and application of technological innovation can reinforce support for environmental protection. Still, they can also reinforce inequalities if data infrastructures, analytical capacity, and decision-making power are concentrated in privileged institutions or areas. The communities most affected by environmental degradation should not be used as data sources. To establish trust and legitimacy, participatory monitoring, Indigenous and local knowledge, open but responsible data practices, and inclusive science–policy interfaces are required. Environmental monitoring should not only provide information about ecological change but also about unequal exposure and vulnerability, as well as access to environmental benefits.

Adaptive, interoperable, transparent, and decision-oriented are therefore the features of future monitoring systems. They should combine data sources and maintain uncertainty and context. They need to use artificial intelligence and digital platforms responsibly, without being opaque or overconfident in technology. They should relate indicators to ecological processes and governance needs, rather than simply choosing them because they are easy to measure. Most importantly, they should establish a feedback loop between what they see and what they do: they should monitor interventions, evaluate interventions, and follow up on the results to make decisions about future actions.

Finally, the data-to-decisions shift calls for a paradigm shift in how environmental monitoring is conceived. The best systems will not necessarily be those with the best-resolution sensor, the largest database, or the most complex model. They will be credible, evidence-based, timely, action-oriented, honest communicators of uncertainty, diverse knowledge-system enablers, and accountable to ecosystems and societies. To realize this vision, coordinated action is urgently needed.

For researchers, priority should be given to developing interoperable, uncertainty-transparent frameworks that link multi-source data to decision thresholds, and to assessing the long-term effectiveness of monitoring-informed interventions. For policymakers, we recommend embedding integrative monitoring into regulatory cycles, mandating open but equitable data governance, and using adaptive management pathways that explicitly connect environmental indicators to enforceable actions. For funding agencies, sustained investment must target cross-disciplinary monitoring infrastructures, capacity-building in data-poor regions, and participatory models that empower local communities as co-producers of environmental knowledge. Integrative environmental monitoring is not merely a technical exercise but a governance imperative for resilience, sustainability, and environmental justice in the Anthropocene. The question is no longer whether we can collect more data, but whether we can build the institutional and social architectures to turn data into accountable, timely, and equitable action.

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References

[1] Ndehedehe, C., 2023. Understanding the Anthropocene. In Hydro-Climatic Extremes in the Anthropocene. Springer International Publishing: Cham, Switzerland. pp. 3–22. DOI: https://doi.org/10.1007/978-3-031-37727-3_1

[2] Malakar, K.D., Kumar, M., Anand, S., et al., 2023. Climate Change and Socio-Ecological Transformation: Applications and Field Narratives. In Climate Change and Socio-Ecological Transformation. Springer Nature: Singapore. pp. 295–374. DOI: https://doi.org/10.1007/978-981-99-4390-6_7

[3] Ascough, J.C., Maier, H.R., Ravalico, J.K., et

al., 2008. Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. Ecological Modelling. 219(3–4), 383–399. DOI: https://doi.org/10.1016/j.ecolmodel.2008.07.015
[4] Rashid, S., Singla, A., Yadav, B., et al., 2025. Tracing Environmental Changes Over Time. In: Sankhla, M.S., Awasthi, K.K., Sharma, T., et al. (eds.). Introducing the Synergy Between Forensic Science and Environmental Analysis. Springer Nature: Singapore. pp. 61–80. DOI: https://doi.org/10.1007/978-981-95-0199-1_4
[5] Biermann, F., 2022. The future of 'environmental' policy in the Anthropocene: time for a paradigm shift. In Trajectories in Environmental Politics. Routledge: London, UK. pp. 58–77. DOI: https://doi.org/10.4324/9781003213321-4
[6] Fascista, A., 2022. Toward Integrated Large-Scale Environmental Monitoring Using WSN/UAV/Crowdsensing: A Review of Applications, Signal Processing, and Future Perspectives. Sensors. 22(5), 1824. DOI: https://doi.org/10.3390/s22051824
[7] Zhao, T., Song, C., Yu, J., et al., 2025. Leveraging Immersive Digital Twins and AI-Driven Decision Support Systems for Sustainable Water Reserves Management: A Conceptual Framework. Sustainability. 17(8), 3754. DOI: https://doi.org/10.3390/su17083754
[8] Russell, B.J., Soffer, R.J., Ientilucci, E.J., et al., 2023. The Ground to Space CALibration Experiment (G-SCALE): Simultaneous Validation of UAV, Airborne, and Satellite Imagers for Earth Observation Using Specular Targets. Remote Sensing. 15(2), 294. DOI: https://doi.org/10.3390/rs15020294
[9] Fraisl, D., Hager, G., Bedessem, B., et al., 2022. Citizen science in environmental and ecological sciences. Nature Reviews Methods Primers. 2(1), 64. DOI: https://doi.org/10.1038/s43586-022-00144-4
[10] Barbierato, E., Gatti, A., 2024. The Challenges of Machine Learning: A Critical Review. Electronics. 13(2), 416. DOI: https://doi.org/10.3390/electronics13020416
[11] Oakes, L.E., Peterson St-Laurent, G., Cross, M.S., et al., 2022. Strengthening monitoring and evaluation of multiple benefits in conservation initiatives that aim to foster climate change adaptation. Conservation Science and Practice. 4(6), e12688. DOI: https://doi.org/10.1111/csp2.12688
[12] Ncube, M.M., Ngulube, P., 2024. Enhancing environmental decision-making: a systematic review of data analytics applications in monitoring and management. Discover Sustainability. 5(1), 290. DOI: https://doi.org/10.1007/s43621-024-00510-0
[13] Cao, S., Hu, X., Wang, Y., et al., 2023. Understanding Spatial-Temporal Interactions of Ecosystem Services and Their Drivers in a Multi-Scale Perspective of Miluo Using Multi-Source Remote Sensing Data. Remote Sensing. 15(14), 3479. DOI: https://doi.org/10.3390/rs15143479
[14] Kissling, W.D., Lumbierres, M., Lyche Solheim, A., et al., 2026. Building the backbone for Europe's biodiversity monitoring. Nature Reviews Biodiversity. 2(4), 242–257. DOI: https://doi.org/10.1038/s44358-026-00140-6
[15] Prasath, C.A., 2025. Big Data-Driven Decision Support System for Urban Climate Adaptation Strategies. Journal of Smart Infrastructure and Environmental Sustainability. 2(2), 65–71.
[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(1), 161–171. DOI: https://doi.org/10.30574/wjarr.2024.21.1.2720
[17] Martinez, J., Mahajan, S., 2024. Redefining Environmental Governance: The Socio-Technical Implications of Open-Source Air Quality Monitoring. SSRN Preprint. DOI: https://doi.org/10.2139/ssrn.4991177
[18] Karagiannopoulou, A., Tsertou, A., Tsimiklis, G., et al., 2022. Data Fusion in Earth Observation and the Role of Citizen as a Sensor: A Scoping Review of Applications, Methods and Future Trends. Remote Sensing. 14(5), 1263. DOI: https://doi.org/10.3390/rs14051263
[19] Dong, J., Liang, X., Du, B., et al., 2025. Applications of Geographic Information Systems in Ecological Impact Assessment: A Methods Landscape, Practical Bottlenecks, and Future Pathways. Sustainability. 17(22), 10358. DOI: https://doi.org/10.3390/su172210358
[20] Talukder, K.A., 2025. The impact of data-driven decision support systems on governance and policy implementation in US institutions. ASRC Procedia: Global Perspectives in Science and Scholarship. 1(1), 994–1030. DOI: https://doi.org/10.63125/3v98q104
[21] Wang, D., Xu, P.-Y., An, B.-W., et al., 2024. Urban green infrastructure: bridging biodiversity conservation and sustainable urban development through adaptive management approach. Frontiers in Ecology and Evolution. 12, 1440477. DOI: https://doi.org/10.3389/fevo.2024.1440477
[22] Ilcic, A., Fuentes, M., Lawler, D., 2025. Artificial intelligence, complexity, and systemic resilience in global governance. Frontiers in Artificial Intelligence. 8, 1562095. DOI: https://doi.org/10.3389/frai.2025.1562095
[23] Nazarov, D., Sulimin, V., Shvedov, V., 2024. Advancing environmental stewardship: The role of automation in enhanced environmental monitoring. E3S Web of Conferences. 542, 05005. DOI: https://doi.org/10.1051/e3sconf/202454205005

[24] Mollenhauer, H., Kasner, M., Haase, P., et al., 2018. Long-term environmental monitoring infrastructures in Europe: observations, measurements, scales, and socio-ecological representativeness. Science of The Total Environment. 624, 968–978. DOI: https://doi.org/10.1016/j.scitotenv.2017.12.095

[25] Thenkabail, P. (ed.), 2018. Remote Sensing Systems—Platforms and Sensors: Aerial, Satellite, UAV, Optical, Radar, and LiDAR. In Remote Sensing Handbook - Three Volume Set. CRC Press: Boca Raton, FL, USA. pp. 37–92. DOI: https://doi.org/10.1201/b19355-8

[26] Pettorelli, N., Schulte To Bühne, H., Tulloch, A., et al., 2018. Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. Remote Sensing in Ecology and Conservation. 4(2), 71–93. DOI: https://doi.org/10.1002/rse2.59

[27] Conrad, C.C., Hilchey, K.G., 2011. A review of citizen science and community-based environmental monitoring: issues and opportunities. Environmental Monitoring and Assessment. 176(1–4), 273–291. DOI: https://doi.org/10.1007/s10661-010-1582-5

[28] Brown, G., Rhodes, J., Lunney, D., et al., 2019. The influence of sampling design on spatial data quality in a geographic citizen science project. Transactions in GIS. 23(6), 1184–1203. DOI: https://doi.org/10.1111/tgis.12568

[29] Narayana, T.L., Venkatesh, C., Kiran, A., et al., 2024. Advances in real time smart monitoring of environmental parameters using IoT and sensors. Heliyon. 10(7), e28195. DOI: https://doi.org/10.1016/j.heliyon.2024.e28195

[30] Darling, J.A., Blum, M.J., 2007. DNA-based methods for monitoring invasive species: a review and prospectus. Biological Invasions. 9(7), 751–765. DOI: https://doi.org/10.1007/s10530-006-9079-4

[31] Velmurugan, T., Manimala, V., Parameshwari, V., et al., 2026. Advanced Signal Processing Techniques in Bioacoustics by Elevating Wildlife Monitoring. In: Subbaraj, K., Balusamy, B., Chithirai Pon Selvan, M., et al. (eds.). Computational Bioacoustic Artificial Intelligence. Springer Nature: Cham, Switzerland. pp. 3–23. DOI: https://doi.org/10.1007/978-3-032-06088-4_1

[32] Yoon, H.J., Seo, J.H., Shin, S.H., et al., 2025. Bioinformation and Monitoring Technology for Environmental DNA Analysis: A Review. Biosensors. 15(8), 494. DOI: https://doi.org/10.3390/bios15080494

[33] Tella, A., Mandu, M., 2025. Ensuring Reliable Data: Innovative Approaches to Metadata Research and Practices. Bibliotechnyi visnyk. (4), 132–145. DOI: https://doi.org/10.15407/bv2025.04.132

[34] Reitz, T., Escriu, J., Minghini, M., 2025. Interoperability Approaches for environmental data sharing and reuse in the European Union. Publications Office of the European Union: Luxembourg, Luxembourg.

[35] Kochanek, A., Generowicz, A., Zacłona, T., 2025. The Role of Geographic Information Systems in Environmental Management and the Development of Renewable Energy Sources—A Review Approach. Energies. 18(17), 4740. DOI: https://doi.org/10.3390/en18174740

[36] Janković, S., 2024. Navigating Uncertainties in the Built Environment: Reevaluating Antifragile Planning in the Anthropocene through a Posthumanist Lens. Buildings. 14(4), 857. DOI: https://doi.org/10.3390/buildings14040857

[37] Goho, S.A., 2023. Advances in Air Monitoring Opportunities and Challenges for Addressing Race, Poverty, and Environmental Justice. American Journal of Law and Equality. 3, 53–63. DOI: https://doi.org/10.1162/ajle_a_00054

[38] Zeng, Y., Hao, D., Huete, A., et al., 2022. Optical vegetation indices for monitoring terrestrial ecosystems globally. Nature Reviews Earth & Environment. 3(7), 477–493. DOI: https://doi.org/10.1038/s43017-022-00298-5

[39] Keyhanipour, A.H., 2026. Uncertainty-aware synthetic data generation: a systematic review of methods and challenges. International Journal of Data Science and Analytics. 22(1), 141. DOI: https://doi.org/10.1007/s41060-026-01120-x

[40] Gabriele, M., Brumana, R., Previtali, M., et al., 2023. A combined GIS and remote sensing approach for monitoring climate change-related land degradation to support landscape preservation and planning tools: the Basilicata case study. Applied Geomatics. 15(3), 497–532. DOI: https://doi.org/10.1007/s12518-022-00437-z

[41] Dritsas, E., Trigka, M., 2025. Remote Sensing and Geospatial Analysis in the Big Data Era: A Survey. Remote Sensing. 17(3), 550. DOI: https://doi.org/10.3390/rs17030550

[42] Brunet, L., 2025. Mapping for Mapping's Sake? Ecosystems Services Maps and the Modes of (Ir)relevance of Ecological Knowledge for Nature Conservation. Minerva. 63(2), 231–255. DOI: https://doi.org/10.1007/s11024-024-09552-0

[43] Koldasbayeva, D., Tregubova, P., Gasanov, M., et al., 2024. Challenges in data-driven geospatial modeling for environmental research and practice. Nature Communications. 15(1), 10700. DOI: https://doi.org/10.1038/s41467-024-55240-8

[44] Jeliazkov, A., Gavish, Y., Marsh, C.J., et al., 2022. Sampling and modelling rare species: Conceptual guidelines for the neglected majority. Global Change Biology. 28(12), 3754–3777. DOI: https://doi.org/10.1111/gcb.16114

[45] Polasky, S., Carpenter, S.R., Folke, C., et al., 2011. Decision-making under great uncertainty: environ-

mental management in an era of global change. Trends in Ecology & Evolution. 26(8), 398–404. DOI: https://doi.org/10.1016/j.tree.2011.04.007
[46] Villegas-Ch, W., García-Ortiz, J., Sánchez-Viteri, S., 2024. Toward Intelligent Monitoring in IoT: AI Applications for Real-Time Analysis and Prediction. IEEE Access. 12, 40368–40386. DOI: https://doi.org/10.1109/ACCESS.2024.3376707
[47] Tironi, M., Rivera Lisboa, D.I., 2023. Artificial intelligence in the new forms of environmental governance in the Chilean State: Towards an eco-algorithmic governance. Technology in Society. 74, 102264. DOI: https://doi.org/10.1016/j.techsoc.2023.102264
[48] Giupponi, C., Ausseil, A.-G., Balbi, S., et al., 2022. Integrated modelling of social-ecological systems for climate change adaptation. Socio-Environmental Systems Modelling. 3, 18161. DOI: https://doi.org/10.18174/sesmo.18161
[49] Little, J.C., Kaaronen, R.O., Hukkinen, J.I., et al., 2023. Earth Systems to Anthropocene Systems: An Evolutionary, System-of-Systems, Convergence Paradigm for Interdependent Societal Challenges. Environmental Science & Technology. 57(14), 5504–5520.
[50] Mir, Y.H., Mir, S., Ganie, M.A., et al., 2025. Overview of Land Use and Land Cover Change and Its Impacts on Natural Resources. In: Jatav, H.S., Raiput, V.D., Minkina, T. (eds.). Ecologically Mediated Development: Promoting Biodiversity Conservation and Food Security. Springer Nature: Singapore. pp. 101–130. DOI: https://doi.org/10.1007/978-981-96-2413-3_5
[51] Padhiary, M., Kumar, R., 2024. Assessing the Environmental Impacts of Agriculture, Industrial Operations, and Mining on Agro-Ecosystems. In: Azrour, M., Mabrouki, J., Alabdulatif, A., et al. (eds.). Smart Internet of Things for Environment and Healthcare. Springer Nature: Cham, Switzerland. pp. 107–126. DOI: https://doi.org/10.1007/978-3-031-70102-3_8
[52] Nugroho, S., Uehara, T., 2023. Systematic Review of Agent-Based and System Dynamics Models for Social-Ecological System Case Studies. Systems. 11(11), 530. DOI: https://doi.org/10.3390/systems11110530
[53] McCarthy, M.J., Herrero, H.V., Insalaco, S.A., et al., 2025. Satellite remote sensing for environmental sustainable development goals: A review of applications for terrestrial and marine protected areas. Remote Sensing Applications: Society and Environment. 37, 101450. DOI: https://doi.org/10.1016/j.rsase.2025.101450
[54] Schönbeck, L., Arteaga, M., Mirza, H., et al., 2023. Plant physiological indicators for optimizing conservation outcomes. Conservation Physiology. 11(1), coad073. DOI: https://doi.org/10.1093/conphys/coad073
[55] Niemeijer, D., De Groot, R.S., 2008. A conceptual framework for selecting environmental indicator sets. Ecological Indicators. 8(1), 14–25. DOI: https://doi.org/10.1016/j.ecolind.2006.11.012
[56] Hazen, E.L., Savoca, M.S., Clark-Wolf, T.J., et al., 2024. Ecosystem Sentinels as Early-Warning Indicators in the Anthropocene. Annual Review of Environment and Resources. 49(1), 573–598. DOI: https://doi.org/10.1146/annurev-environ-111522-102317
[57] Beven, K., 2018. Environmental Modelling: An Uncertain Future? CRC press: London, UK.
[58] Sebok, E., Henriksen, H.J., Pastén-Zapata, E., et al., 2022. Use of expert elicitation to assign weights to climate and hydrological models in climate impact studies. Hydrology and Earth System Sciences. 26(21), 5605–5625. DOI: https://doi.org/10.5194/hess-26-5605-2022
[59] Guillen-Aguinaga, M., Aguinaga-Ontoso, E., Guillen-Aguinaga, L., et al., 2025. Data Quality in the Age of AI: A Review of Governance, Ethics, and the FAIR Principles. Data. 10(12), 201. DOI: https://doi.org/10.3390/data10120201
[60] Nilsson, M., Persson, A., 2003. Framework for analysing environmental policy integration. Journal of Environmental Policy & Planning. 5(4), 333–359. DOI: https://doi.org/10.1080/1523908032000171648
[61] Chatrabhuj, Meshram, K., 2024. Design of an iterative method for environmental-sustainable development: Integrating bioinspired computing techniques. Environmental Development. 51, 101045. DOI: https://doi.org/10.1016/j.envdev.2024.101045
[62] Sarker, S., 2025. Role of management information systems in environmental risk assessment: A systematic review of geographic and ecological applications. American Journal of Interdisciplinary Studies. 6(1), 95–126. DOI: https://doi.org/10.63125/k27tnn83
[63] Filip, F.G., 2022. Collaborative Decision-Making: Concepts and Supporting Information and Communication Technology Tools and Systems. International Journal of Computers Communications & Control. 17(2). DOI: https://doi.org/10.15837/ijccc.2022.2.4732
[64] Yang, Y., Shen, L., Li, Y., et al., 2022. The Impact of Environmental Information Disclosure on Environmental Governance Satisfaction. Sustainability. 14(13), 7888. DOI: https://doi.org/10.3390/su14137888
[65] Shirk, A.J., Jones, G.M., Yang, Z., et al., 2023. Automated habitat monitoring systems linked to adaptive management: a new paradigm for species conservation in an era of rapid environmental change. Landscape Ecology. 38(1), 7–22. DOI: https://doi.org/10.1007/s10980-022-01457-1
[66] Digkoglou, P., Papathanasiou, J., 2025. Application of multiple criteria decision aiding in environmental policy-making processes. International Journal of Envi-

ronmental Science and Technology. 22(8), 6967–6982. DOI: https://doi.org/10.1007/s13762-024-06101-w

[67] Gupta, P., Tandekar, K., Mirjha, S.T., et al., 2025. Early Warning Systems: Timely Responses to Extreme Weather Events. In Global Climate Stress on Crop Improvement and Management. CRC Press: London, UK. pp. 436–461. DOI: https://doi.org/10.1201/9781003750437-15

[68] Singh, S.K., Gothania, J., Sansaniwal, S.K., 2026. Early Warning Systems and Real-Time Decision Support: Leveraging GIS and Remote Sensing for Global Disaster Preparedness. In: Guney, İ., Celik, M.A. (eds.). Interdisciplinary Studies on Global Disasters. IGI Global Scientific Publishing: Hershey, PA, USA. pp. 373–398. DOI: https://doi.org/10.4018/979-8-3373-6274-8.ch013

[69] Moallemi, E.A., Gao, L., Eker, S., et al., 2022. Diversifying models for analysing global change scenarios and sustainability pathways. Global Sustainability. 5, e7. DOI: https://doi.org/10.1017/sus.2022.7

[70] Flörke, M., Wimmer, F., Laaser, C., et al., 2011. Climate Adaptation–Modelling Water Scenarios and Sectoral Impacts. CESR – Center for Environmental Systems Research: Kassel, Germany.

[71] Gregory, R., Failing, L., Higgins, P., 2006. Adaptive management and environmental decision making: A case study application to water use planning. Ecological Economics. 58(2), 434–447. DOI: https://doi.org/10.1016/j.ecolecon.2005.07.020

[72] Sahu, Y., Upadhyay, V.K., 2024. Environmental Application of Digital Twins: A Review. In: Talukdar, S., Rahman, A., Bera, S., et al. (eds.). Environmental Risk and Resilience in the Changing World. Springer Nature: Cham, Switzerland. pp. 287–295. DOI: https://doi.org/10.1007/978-3-031-62442-1_18

[73] Morchenko, A.A., 2025. Cognitive Efficiency in Environmental Dashboards: Bridging Visual Perception Theory and Spatiotemporal Sustainability Monitoring. SciQuest Research Database. 5(10), 79–86.

[74] Wesselink, A., Buchanan, K.S., Georgiadou, Y., et al., 2013. Technical knowledge, discursive spaces and politics at the science–policy interface. Environmental Science & Policy. 30, 1–9. DOI: https://doi.org/10.1016/j.envsci.2012.12.008

[75] Huitema, D., Turnhout, E., 2009. Working at the science–policy interface: a discursive analysis of boundary work at the Netherlands Environmental Assessment Agency. Environmental Politics. 18(4), 576–594. DOI: https://doi.org/10.1080/09644010903007427

[76] Andersson, K., Boyes, C., Richards, K., 2023. Diagnosing environmental problems and their possible policy responses: A tool for assessing initial options. Elem Sci Anth. 11(1), 00137. DOI: https://doi.org/10.1525/elementa.2022.00137

[77] Keenleyside, K., 2012. Ecological Restoration for Protected Areas: Principles, Guidelines and Best Practices. IUCN (International Union for Conservation of Nature): Gland, Switzerland.

[78] Brock, T., Reed, M.G., Stewart, K.J., 2023. A practical framework to guide collaborative environmental decision making among Indigenous Peoples, corporate, and public sectors. The Extractive Industries and Society. 14, 101246. DOI: https://doi.org/10.1016/j.exis.2023.101246

[79] Cooke, S.J., Cook, C.N., Nguyen, V.M., et al., 2023. Environmental evidence in action: on the science and practice of evidence synthesis and evidence-based decision-making. Environmental Evidence. 12(1), 10. DOI: https://doi.org/10.1186/s13750-023-00302-5

[80] Pujar, G.S., Taori, A., Chakraborty, A., et al., 2024. Sensing Climate Change Through Earth Observations: Perspectives at Global and National Level. In: Priyadarshan, P.M., Jain, S.M., Penna, S., et al. (eds.). Digital Agriculture. Springer International Publishing: Cham, Switzerland. pp. 225–280. DOI: https://doi.org/10.1007/978-3-031-43548-5_8

[81] Aubrecht, C., Özceylan, D., Steinnocher, K., et al., 2013. Multi-level geospatial modeling of human exposure patterns and vulnerability indicators. Natural Hazards. 68(1), 147–163. DOI: https://doi.org/10.1007/s11069-012-0389-9

[82] Sharma, T., Singh, A., Kumar, N., et al., 2023. Emerging Pollutants in the Environment and Ecological Risks. In: George, N., Dwibedi, V., Rath, S.K., et al. (eds.). Management and Mitigation of Emerging Pollutants. Springer International Publishing: Cham, Switzerland. pp. 1–20. DOI: https://doi.org/10.1007/978-3-031-41005-5_1

[83] Arriazu-Ramos, A., Santamaría, J.M., Monge-Barrio, A., et al., 2025. Health Impacts of Urban Environmental Parameters: A Review of Air Pollution, Heat, Noise, Green Spaces and Mobility. Sustainability. 17(10), 4336. DOI: https://doi.org/10.3390/su17104336

[84] Verburg, P.H., Mertz, O., Erb, K.-H., et al., 2013. Land system change and food security: towards multi-scale land system solutions. Current Opinion in Environmental Sustainability. 5(5), 494–502. DOI: https://doi.org/10.1016/j.cosust.2013.07.003

[85] King, D., Gurtner, Y., 2025. Information and communication for disaster resilience. Australian Journal of Emergency Management. 40(3), 17–28. DOI: https://doi.org/10.47389/40.3.17

[86] Tiggeloven, T., Raymond, C., De Ruiter, M.C., et al., 2026. Multi-hazard risk assessment and management: pathways for the Sendai Framework and beyond. Geoscience Communication. 9(2), 185–221. DOI: https://doi.org/10.5194/gc-9-185-2026

[87] Adepoju, A.H., Austin-Gabriel, B., Hamza, O., et al., 2022. Advancing monitoring and alert systems: A proactive approach to improving reliability in complex data ecosystems. IRE Journals. 5(11), 281–282.