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REVIEW

From Smart Data to Sustainable Decisions: Intelligent Technologies in Environmental Monitoring and Resource Management

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ABSTRACT

The rapid advancement of intelligent technologies, such as machine learning, optimization algorithms, and decision support systems (DSS), presents significant opportunities for improving environmental monitoring and resource management. Such technologies are able to handle large, complicated datasets to deliver actionable insights that are able to support sustainable decision-making. Nonetheless, data quality, model reliability, model uncertainty, and stakeholder participation are important issues that should be considered carefully during the transformation of raw environmental data into informed decisions. The review describes the application of intelligent systems to different contexts of environmental decisions, such as compliance and enforcement, early warning systems, resource allocation, and conservation planning. We argue that these systems must be reliable and fair, highlighting the importance of data governance, transparency, and ethical considerations. We also discuss the practical demands of being deployed in the real world, including the interoperability of the data, adapting the model to new circumstances, and the financial and technical constraints of deploying the more sophisticated technologies. Based on case studies, we determine not only the achievements but also the drawbacks of the existing applications, providing information on how intelligent technologies could be better combined into the decision-making process. In conclusion, we present a research and policy agenda wherein we would focus on integrating the system, assessing the model continuously, and involving a wide range of stakeholders to make sure that these technologies are used in a way that enhances environmental sustainability and social equity.

Keywords: Intelligent Technologies; Environmental Decision-Making; Data Governance; Machine Learning; Sustainability

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1. Introduction

In the present, environmental sustainability is increasingly characterized as making choices based on complex dynamic systems [1]. Monitoring and evaluation of environmental conditions have been greatly enhanced by the development of remote sensing, data collection technologies, and sensor networks, which give us real-time and granular information on the quality of air, water resources, land use, and biodiversity [2,3]. Satellites obtain images on the peripheries of space, drones and in-situ sensors present localized data, and crowdsourced information from citizens offers rich inputs with context. Although the amount of environmental data has grown by an enormous amount, the issue is not how to get more data but how to make decisions that are at the right time, practical, and, more importantly, sustainable. It is no longer about how we can measure more but how we can make these measurements helpful, effective, and fair.

The core of this change is the idea of smart data [4]. Whereas big data is simply described as data in large amounts, smart data has the quality, context, and wisdom applied to making decisions. Information is insufficient, but these measurements need to be transcended, put in context, and recorded in a way that can be used by decision-makers. Environmental data are never homogeneous spatially and temporally, accurate, and available. An example of this is satellite images, which can differ greatly in terms of their resolution, frequency, and type of measurements, i.e., optical versus radar measurements. The in-situ sensors may be prone to calibration drift and biases in their location, and crowdsourced data, despite its value, may not be available in some areas. Hence, to be useful to the decision-makers, these datasets should not only be accurate but also have metadata and provenance, as well as clearly indicated uncertainty.

Besides, the information should be optimized to the requirements of the decision-makers, delivering the appropriate information at the appropriate time and in an appropriate format. Environmental choices, whether it is in land management, water allocation, disaster management, or pollution control, are time-sensitive and in many cases, high-stakes choices [5,6]. The reaction of a city to air quality pollution, e.g., is dependent on timely measurements that are precise enough to activate public health alerts. On the same note, water allocation decisions made in the event of drought rely on accurate predictions of the streamflow and reservoir levels. Thus, data should not only be correct, but also timely, and their updating has to be of a frequency that will facilitate the decision-making processes going on.

Nevertheless, data quality is not the only issue, as the problem of converting raw data into actionable, sustainable decisions is present. The technologies employed to process this data have to be smart. The tools included in intelligent technologies are extremely diverse: there are machine learning algorithms discovering patterns in multifaceted datasets, there are spatiotemporal models that enable forecasting the future of the environment, and there are optimization techniques that allow allocating resources effectively. Decision support systems (DSS) are also included in such technologies, and they combine models with expert judgment and give actionable recommendations. These systems are not merely aimed at coming up with correct forecasts but also at giving actionable advice to decision-makers. It is thus not enough that intelligent systems do not just have the ability to process heavy amounts of data, but also have the ability to do so in a manner that can be used in the practical decision-making process [7].

Model performance is not the only factor that determines the effectiveness of intelligent technologies in environmental decision-making. Such technologies should be strong, understandable, and readable [8,9]. Environmental systems tend to be dynamic, and the conditions of a system change over time and might not be recorded in the past or may not be modeled to reflect reality. Models that have been trained to work on data in a given period cannot be effective in a scenario where the system is subjected to changes in climate, land cover, or technology. Decision-makers, hence, should know how the models may perform in new situations and where they may fail. Also, any decision arrived at through these models should be transparent, especially where the citizens think of the greater good of the people. To illustrate this, in the context of compliance and enforcement, the stakeholders have to be capable of comprehending why and how a specific area is identified to be checked or why a specific policy is suggested.

The social and political implications of environmental decisions are also of great concern. They tend not just to be technical, but also value-based, having consequences of equity and justice. Take the example of water resource management in times of drought. One model could pre-empt the necessity of water limitation, yet the question of whom this limitation will be imposed upon, i.e., agriculture, industry, or residential zones, may be controversial. On the same note, environmental laws focused on pollution do not favor some groups of people more, especially those who are marginalized. These are decisions that should be made keenly without any form of unfairness. Thus, intelligent technologies should be designed taking into consideration not only the technical performance of models, but also social and ethical concerns [10].

Although the development of intelligent technologies to monitor the environment and manage the resources seems promising, there is still something missing between the data and the decisions that they are supposed to make. In most instances, these technologies are created within research environments and are unable to cross the gap into the working environment. One major problem with this is the last-mile problem: whereas advanced models can work well in controlled cases, they can generally fail in actual circumstances. Models also find it hard to keep up with the complexities of the operational environment, where there is noise in data, decisions should be made quickly, and models should be constantly updated to encompass new information [11,12].

This review aims at analyzing this important gap with respect to environmental decision-making. It dwells on the ability of intelligent technologies, that is, machine learning, optimization, and decision support systems, to be implemented in the real-world environment to enhance sustainability outcomes [4,9,13]. The review points to the necessity of decision-aligned technologies, which, in addition to being accurate, should be interpretable, robust, and fair. It also highlights the significance of practices of governance and data management leading to high-quality data, transparency, and accountability. In addition, it emphasizes that there needs to be a change in how we determine the effectiveness of such technologies. Conventional measures of model performance, e.g., accuracy or precision, are not adequate. Rather, we have to quantify the effect of these technologies on the outcome of decisions, taking into account such factors as the minimization of risks, cost-effectiveness, and equity.

This review is aimed not only at studying the state-of-the-art technologies and methodologies but also at the framework of their application in the decision-making process. This review will be used to offer action-oriented information to practitioners, policymakers, and other researchers interested in the topic of the use of smart data and intelligent systems to help them make sustainable decisions. It is on this analysis that we will seek to enlighten the avenues under which smart technology can be used to facilitate meaningful and fair environmental deliverables.

The following sections will discuss the various decision scenarios in which the technologies are implemented, the importance of data governance to make sure that the systems in which they are implemented are reliable and accountable, challenges, and opportunities that can be presented by introducing intelligent technologies on a large scale. We shall also examine the case studies and impact evidence to outline the practical implications of such systems implementation and provide recommendations for future research and policy formulation. Finally, the purpose of this review is to have a broad knowledge of what role can be played by the use of intelligent technologies in order to promote sustainability, and a roadmap on what can be done to overcome the obstacles that limit their full potential.

2. Decision Contexts and Stakeholders

Within the framework of environmental surveillance and resource management, the effectiveness of the intelligent technologies depends on the clear vision of the decision situations in which they will ultimately be implemented and the actors of the decision-making process [13]. Decisions that are related to environmental issues are not homogeneous, and they have diverse areas, times, and scopes of application based on a specific challenge under consideration. It could be reacting to a short-term air quality alert, long-term water management during a drought, or large-scale ecosystem restoration; the form of decision to be made will determine the most effective data requirements, modeling methods, and technologies. Having these contexts in place and the interests and capacities of the stakeholders concerned is critical in putting smart data into practical decisions that favor sustainability results.

2.1. Decision Types across Governance Levels

The environmental decisions can be divided based on their time horizons and operational environments. These choices are a wide range, both reactive in response to current events and long-term, strategic planning. At the operational level, there is also a tendency to make decisions based on direct concerns and respond promptly and on the ground. Examples can be the release of a health advisory after the air quality is poor, the implementation of emergency response teams to curb wildfires, or the activation of flood mitigation measures, which are based on real-time data. Such decisions are often characterized by monitoring and detection technologies that can track and determine the risk within a short period and present the information to decision-makers to take action now [14].

Tactical decisions, in their turn, have a slightly longer time scale, which is usually in weeks or months [15]. In this level, the decision-makers can be seen to assign resources, plan interventions, and make more specific judgments regarding the manner in which risks will be managed. An example of managing water resources during a drought is to strike a balance between various competing interests: agriculture, industry, and domestic use. Such decisions can be based on predictive models and optimization software to determine the availability of resources and manage the efficient capacity of limited resources. Equally, in case of a wildfire, the priority areas of fuel reduction can be the tactical decision instead of areas where the concentration of firefighting resources can be applied to reduce risk.

At the strategic level, the decisions are related to policy formulation and long-term planning, which might have an impact for decades [16]. Such choices reflect the future path of managing the environment and resource exploitation strategy, including land-use planning, climate change mitigation strategies, or even the way urban infrastructure is designed to be able to respond to changing weather patterns. Strategic decisions need to have a bigger perspective and are usually made through a mixture of modeling, scenario analysis, and consultation with stakeholders in order to have an awareness of the possible effects of different courses of action. These choices can be complicated and require considering more than one objective, e.g., a desire to maximize the growth of the economy and minimize the destruction of nature, or make sure that the policies are fair and equitable.

2.2. Stakeholder Mapping and Interests

Sound environmental decision-making also requires the knowledge of the various groups of stakeholders that are involved in the process, with each having different perspectives, incentives, and power involved in the exercise [17]. These stakeholders include government agencies, non-governmental organizations (NGOs), industry players, the local communities, and the general population. The contribution of each of the stakeholders and the priorities they have could considerably affect the kind of data and technology applied in the decision-making process.

The government agencies, both local and national governments, are often the major decision makers in environmental management [18]. The agencies create and enforce the policies and make sure that the environmental laws and regulations are adhered to. As an example, the regulatory bodies can use environmental surveillance systems as a way of monitoring pollution levels or monitoring the effectiveness of conservation efforts. These stakeholders are interested mostly in compliance, risk management, and even equal sharing of the environmental benefits and burdens. Moreover, the government agencies might experience constraints in terms of budget, which determines what type of technologies can be implemented and the level of maintenance.

Another stakeholder is the NGOs and advocacy groups. Such organizations are usually a product of marginalized groups, environmental conservation interests, or a given ecosystem or species. NGOs can demand more effective protection, insist on incorporating the issue of environmental justice, and keep an eye on the effects of industrial operations. Their participation in the decision-making process tends to focus on accountability, transparency, and participation by the people. These organizations may be instrumental in seeing to it that the information that comes as a result of the monitoring is employed in championing policies that safeguard the vulnerable groups and the environment [19,20].

The role of the private sector also takes center stage, especially in agriculture, energy, and manufacturing sectors, among others [21]. Firms within such industries can apply intelligent technologies to streamline their resource consumption, emission cuts, or environmental standards. But in most cases, their interests are influenced by cost-efficiency and profitability. Even though companies can take advantage of the advanced monitoring and resource management technologies, they can also be opposed to some of the policies that restrict their operations or increase the costs. Hence, the capacity of smart technologies to meet or conflict with the interests of the business world may be a determining factor in their performance to promote sustainable results.

The closest stakeholders in most environmental decisions are the local communities and the general population [22]. As an example, when it comes to water resource management, a change in the manner in which water allocations are determined can have a direct effect on farmers, urban inhabitants, and local industries. On the same note, communities residing in regions that are likely to be affected by natural disasters like floods, wildfires, or hurricanes would be especially impacted by early warning systems or disaster preparedness plans. Early involvement of these stakeholders in the process of decision-making is vital in making sure that the concerns of these parties are considered and the technologies implemented are deemed valid and credible. The involvement of the public may also allow an improved collection of data, including citizen science initiatives, and make sure that the decisions are made inclusively and fairly.

2.3. Understanding What Decision-Makers Need from Intelligence

There are particular needs of each type of decision-maker regarding what data and technologies should be offered to facilitate their decision-making. At the operational level, the decision-makers tend to give preference to information that is real-time and can enable them to make decisions in a hurry. To illustrate, a health agency that controls air quality in a city requires almost real-time information concerning the concentration of pollutants in an area to give out health alerts or to change traffic flows. Under these circumstances, the first requirement is correct, well-updated measurements, which are easily interpretable and can be taken into action [23].

To the tactical and strategic decision-makers, the intelligence requirement is no longer real-time but predictive, which can be used in the future [16]. In water management, as one example, the agencies should know the impact of the climate movement and variations in seasons on water availability in the coming months. In this case, decision-makers also need forecasting models capable of giving them an approximation of the water level or demand, and also an optimization tool that would assist them in allocating resources most effectively. Equally, long-term scenarios are required by strategic decision-makers working in land-use planning or conservation initiatives in order to evaluate the potential effect of various interventions, including modifications in land zoning, biodiversity protection policies, or carbon capture activities.

Nonetheless, uncertainty quantification is a typical requirement of all decision-makers, irrespective of the time horizon. The nature of environmental systems is uncertain because of their complexity and shortcomings in monitoring technologies. The decision-makers need direct, practical estimates of uncertainties to enable them to determine the risks involved in different actions. As an example, when responding to an emergency in a region with a potential for a wildfire in a residential community, knowledge of the likelihood of fire spreading will assist decision-makers in prioritizing resources appropriately. On the same note, during policy design, uncertainty in forecasts has the potential to inform risk-aversion policies to defend against worst-case risks [24].

Notably, the tools that enable interpretability and transparency are also necessary for decision-makers [25]. Although advanced models can give very accurate predictions, decision-makers need to know the assumptions, constraints, and sensitivities of these models so as to make sound and defensible decisions. Black box models, in which the outputs provided by the model are not explained, may be counterproductive to getting people to trust them and adopt them, especially in regulatory or other public contexts.

2.4. The Decision Translation Gap

Even with the existence of sophisticated technologies, numerous intelligent systems are yet to be incorporated into the entire decision-making procedures [9,25]. Such a continued difference between the creation of models and their application in decision-making can be explained by various factors. First, the situation of incompatible data and decision situations is quite frequent. Although models can be constructed to provide answers to research questions or to provide predictions using previously available historical data, they might not be consistent with the requirements or limitations of the decision-making processes. As an illustration, a model that has been trained on historical weather patterns might fail to capture future shifts in climate, resulting in the unreliability of the future predictions made by the model to the long-term planner.

Additionally, a considerable number of decision-makers are not tech-savvy enough to read complex models or machine learning algorithms [26]. As much as data scientists might come up with advanced tools, such tools are not always available to the non-expert stakeholders who require them the most. It is important to ensure that these technologies are friendly and incorporated into the decision-making processes to address the translation gap. The stakeholders should also have the assurance that the tools they use are correct and capable of withstanding alterations and can be reconfigured to suit changing circumstances.

Also, there are no universal models of assessment and comparison of various technologies, so decision-makers struggle to find the appropriate tools to make the necessary decisions [27]. That there are no standard best practices of applying these technologies in a real-world environment implies that they may be unwilling to apply the latter, particularly when they are not confident about their long-term reliability and functionality. The only way through such barriers is to ensure that these technologies are tested, verified, and analyzed in real-world scenarios.

3. Smart Data Foundations for Accountable Decisions

The ability to convert crude environmental data into information that can be acted upon and yield a decision is the key to the successful application of smart technologies in environmental monitoring and the management of resources [28,29]. Practically, various types of data related to environmental conditions are gathered: satellites, terrestrial sensors, drones, mobile devices, citizen science, and so on. These measurements can be useful in revealing a great deal about various phenomena of interest concerning the environment, yet they also have inherent problems. To make such datasets useful in decision-making, there should be processes ensuring that they are of high quality, consistent, and relevant to the decision situation. This includes preprocessing of data, integrating the data, governing the data, and also taking into consideration the uncertainties of the measurements. It is only when these fundamental attributes of data management are considered that the environmental monitoring systems are capable of providing the smart data that is necessary to make accountable and transparent decisions.

3.1. Data Sources and Integration for Decision Readiness

The environmental monitoring systems are based on a diverse range of data sources, which has its advantages and shortcomings [30]. An example of such innovations includes satellite remote sensing, which is essential due to its global coverage and helpful information regarding land use, vegetation health, water quality, and atmospheric conditions, among other factors. Satellite data are usually, however, limited in both space and time resolution, thereby limiting their usefulness in capturing local or fast-changing events. Conversely, in-situ sensors are sensors deployed on the ground, in water bodies, or in the air, and provide high spatial resolution and real-time measurements, but could be limited by geographic coverage and maintenance problems. Unmanned Aerial Vehicles (UAVs) and drones are able to provide high-quality images of local areas and are frequently restricted by the range and environmental factors.

Besides these classic techniques of surveillance, mobile sensors and citizen science projects have become more evident over the last few years [31]. The unproven sensors that are inexpensive can be effectively used by the citizens or local organizations, and can greatly increase the coverage of monitoring, particularly in underrepresented or inaccessible locations. Nevertheless, such data sources have an increased susceptibility to errors because of lower standards of calibration, data validation, and inconsistent reporting. Although these sources provide a useful local insight, the main problem is to unify these various sources into a unified and correct decision-making model. Because readiness to make decisions can be largely related to the integration of complementary sources instead of enhancing a single sensor, **Figure 1** illustrates how multi-source fusion and assimilation can turn the heterogeneous inputs into consistent and decision-grade products.

In order to come up with smart data, the raw data of all these different sources will then have to be combined into one coherent system, which guarantees compatibility and consistency across a number of platforms [32]. The challenges presented by heterogeneous datasets require the use of data fusion techniques, which combine the information of other sources to give a complete and more accurate picture of environmental conditions. As an illustration, satellite imagery can be merged with ground sensor measurements by the fusion technique, which allows a more precise evaluation of environmental phenomena, e.g., air pollution or soil moisture. Spatial and time alignment of data is also a part of this process since satellite imagery can be acquired at various times or resolutions than ground-based data. Using such sources, decision-makers are in a position to get more detailed and credible data that is more relevant to the environment.

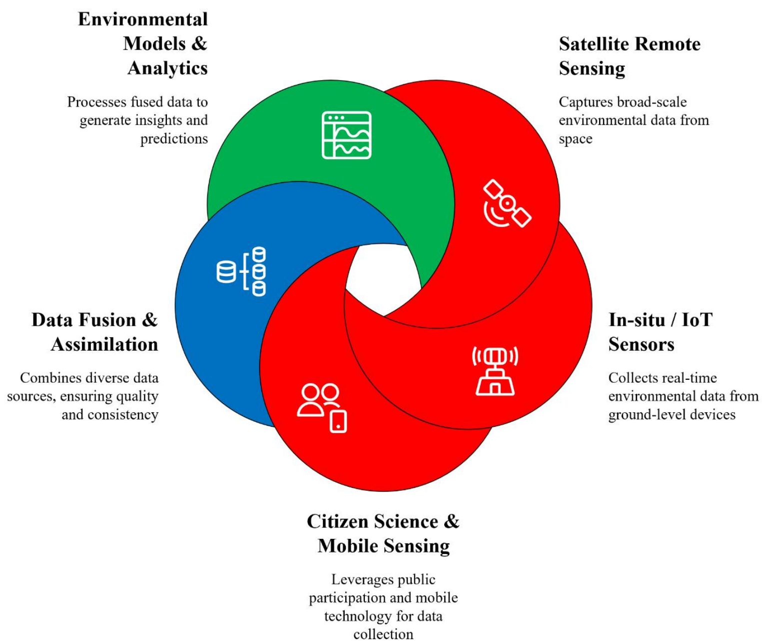

Figure 1. Data integration and fusion in environmental systems: Conceptual schematic linking remote sensing, in-situ sensing, citizen science, and models to harmonized smart-data products for analytics and decision support.

3.2. Data Quality, Representativeness, and Bias

Although smart data will require data integration, the quality and representativeness of the data are also crucial [33]. Environmental data is prone to any form of error, which may include sensor calibration drift, missing or incomplete data. Atmospheric conditions, sensor limitations, and environmental noises may contribute to the errors of measurements by influencing the accuracy of the data collected by remote sensing. Although in-situ sensors provide more resolution and real-time, they may have problems and drift, wear and tear, or poor positioning, which also may affect the quality of data even more.

The other significant difficulty is to make sure that the data that is obtained is a reflection of the true environmental conditions. Environmental data are always spatially and temporally heterogeneous, i.e., the data gathered at one place might not be representative of other places having different environmental conditions [34]. By way of example, air quality measurements at one urban location might not accurately represent the conditions in a nearby industrial locality or the countryside. Just as is the case with ground-based sensors, the sensors can be constrained by the type of locations where they are installed, and therefore, they may not be able to record the entire variability of the environment. Consequently, sampling bias and data representativeness may greatly affect the quality and reliability of the information to be used in decision-making.

These problems can only be corrected through strong data validation and quality control systems. It incorporates the methods of identifying and correcting sensor readings errors, and methods of filling gaps in the data when some measurements are missing or incomplete. The calibration protocols are necessary to make sure that the sensor data are consistent and similar among the instruments and between the deployment periods. Moreover, additional context to interpret the environmental measurements can be achieved by incorporating auxiliary data, including meteorological data or geographic information system (GIS) layers, which are likely to increase the representativeness of the data [35].

The vagueness of the environmental data is one of the unavoidable qualities of the monitoring systems, which should be calculated and reported to the decision-makers [36]. The extent of uncertainty in the data may be due to many factors, such as the capacities of the sensors, the resolution of the satellite shot, and the techniques of analyzing and interpreting the information. The decision-makers should be aware of the degree of uncertainty surrounding the information that they are working with because it directly works to affect their actions. To illustrate this, the prediction of the probability of a flood by a certain model can be less or more uncertain depending on the quality and quantity of the data used. Unless uncertainty is well considered, decision-makers have a tendency to make overly optimistic predictions, thus making bad decisions that might cost them a lot.

3.3. Governance of Data as a Policy Instrument

In addition to technical issues related to data quality and integration, good governance is an important factor in the development of smart data systems to make environmental decisions [37]. Here, governance is a set of policies, standards, and practices that are used to manage data in a proper manner, document it, and make it available to the stakeholders. The administration of data transparency is critical to the proper and ethical use of data, especially when the data are used to make decisions with considerable social, financial, and environmental impact.

Data governance is a multi-dimensional concept that entails the provision of data privacy, security, and access [38]. Environmental information is often sensitive, especially where vulnerable populations or proprietary technology are involved or where national security is a key issue. Access control policies using data should provide a balance between the transparency and openness requirements and the confidentiality of the data. This is especially the case when using citizen-generated data or mobile sensor data, which might have privacy issues regarding the personal use or location-based data.

Another very important aspect of governance is data provenance, or tracking data from its collection to analysis [39]. Stakeholders need to be in a position to trace the manner in which data were collected, processed, and analyzed to be able to trust and utilize data in the process of making decisions. Provenance information contains metadata that gives a background on the methodology, calibration, and quality control operations that are linked to the data. Recording these features will enable decision-makers to evaluate the data's reliability and come up with accurate decisions concerning their applicability to a particular use.

In addition, since environmental data is frequently produced and used by several organizations, data sharing and interoperability should have distinct standards [40,41]. Standards like the FAIR principles (Findability, Accessibility, Interoperability, and Reusability) also make sure that data is easily accessible, compared, and integrated across the various platforms and stakeholders. The interoperability of various data systems enables decision-makers to combine the information found on various sources, such as governmental agencies, research institutions, and private companies, in order to make more comprehensive and informed decisions.

3.4. Decision-Grade Datasets and Reporting

The last stage of changing raw environmental data to smart data is the generation of decision-grade datasets. Decision-grade datasets can be defined as those that have been curated, cleaned, and formatted in order to support particular decision-making processes [42]. These data sets should be well defined in relation to the variables they depict, the level they are operating in, and the frequency within a period over which the data are being reported. As an example, a decision-grade dataset on flood risk management may consist of time-series data on river discharge, precipitation forecasts, and land use changes, all presented in a format that satisfies the requirements of the decision-maker of the flood management agency.

The authority of decision-grade datasets is among the most important features since the datasets are well-documented with a description of the provenance, quality, and constraints of the data [43]. Such documentation is also vital in making sure that the data are utilized in the proper manner and that their constraints are made known to the decision-makers. Besides metadata, decision-grade data sets must have uncertainty estimates, that enables the decision-makers to understand how reliable the data is and what risks different courses of action are likely to have.

Since the use of environmental data is becoming more and more popular to guide policy decisions, the quality of data reporting on such datasets should be high in terms of transparency and accountability [44,45]. The decision-grade datasets have to be made available in formats that can be easily understood by an extremely broad audience consisting of the representatives of the government and industry, as well as the local communities and the population. Clarity and consistency in reporting structures would allow the decision-makers to assess trade-offs, the consequences of their decisions, and explain to the public their reasoning. Finally, the process of generating smart data to make decisions should be holistic, i.e., combining data quality controls, governance, and documentation with the demands of the decision-makers. It is upon these underlying steps that only the environmental monitoring systems can evolve beyond mere data collection to play a significant role in the sustainable management of natural resources. The observation-to-action pathway is most conceptually considered an end-to-end socio-technical pipeline and not a model; **Figure 2** illustrates the interactions of sensing, smart-data processes, analytics, and decision support via feedback and governance.

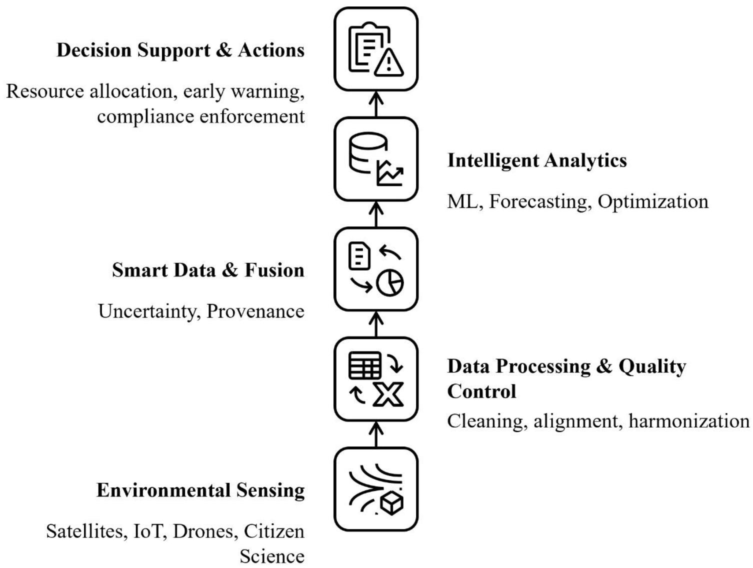

Figure 2. End-to-end process from environmental sensing to sustainable decisions, highlighting data preparation, fusion, modeling, uncertainty handling, decision support, and feedback loops.

4. Mapping Intelligent Technologies to Decision Pathways

The success of intelligent technologies in the environmental decision-making process is determined by the capability of these systems to provide actionable insights using complicated and heterogeneous data [28,46]. Although uncooked facts from different sources of monitoring give a picture of the surrounding environment, it is the intelligent technologies managed over these data sets that make it possible to make meaningful decisions. These technologies include a very broad set of tools, including machine learning and statistical models, optimization algorithms, and decision support systems, each of which is applicable in different situations, based on the nature of the decision made. Placing these technologies on particular environmental decision paths is imperative in making sure that relevant tools are employed to solve the relevant challenges in a manner that will yield the highest chance of sustainability results.

4.1. A Decision-to-Technology Taxonomy

Decisions in the context of environmental management are usually categorized in terms of purpose, scale, and span [47]. These considerations define which kinds of smart technologies can be the most effective in supporting the decisions to be made. The initial process in mapping intelligent technologies to decision pathways is to first classify the intelligent technologies in terms of the decision to which they relate. There are four major decision types of environmental management, namely compliance and enforcement, early warning and resilience, planning and allocation, and restoration and conservation. All of these types of decisions demand different types of data and model deliverables and have different degrees of computational complexity. In order to render the decision-centric structure explicit, **Table 1** is used to map core environmental decision pathways to the intelligent technologies and data inputs that are the most frequently used to support them.

Table 1. Mapping of environmental decision types to typical intelligent technologies and key data inputs used in environmental monitoring and resource management.

Decision Type	Description	Typical Intelligent Technologies	Key Data Inputs
Compliance & Enforcement	Identifying and addressing violations of environmental regulations	Detection algorithms, Classification models, Real-time data monitoring systems	Pollutant levels, emissions data, water quality
Early Warning & Resilience	Predicting and responding to environmental hazards (e.g., floods, wildfires)	Time-series forecasting, Machine learning (RNN, LSTM), Simulation-based models, DSS	Weather data, river discharge, historical hazard data
Resource Allocation & Planning	Optimizing the use of natural resources (e.g., water, land, energy)	Optimization algorithms, Linear programming, Genetic algorithms, Simulation-based optimization	Resource availability, demand forecasts, environmental flow models
Conservation & Restoration	Long-term ecosystem management and biodiversity protection	Multi-objective optimization, Predictive models, Environmental flow models, Digital twins	Ecosystem services data, species distribution models, land-use data

Note: RNN, recurrent neural network; LSTM, long short-term memory (Network).

The decisions on compliance and enforcement are usually concerned with the determination of the cases in which the regulations or the standards are violated and the corrective measures that should be implemented. An example would be the monitoring of an air quality management authority in places where the amounts of pollutants are greater than the acceptable levels, or a water management body would monitor illegal water extraction in protected aquifers. The decision-making based on intelligent technologies tends to be based on detection algorithms, classification models, and real-time information. These systems can include machine learning functions to indicate possible violations based on trends in the data or statistical limits and should be engineered to accept real-time or near-real-time environmental data [48].

When the environment presents hazards that could destroy human lives and property, like floods, wildfires, or storms, early warning and resilience decisions are made [49]. These decisions are based on forecasting models that forecast the probability and severity of certain hazards. The applications typically involve machine learning and time-series models, including recurrent neural networks (RNNs) and temporal convolutional networks (TCNs), because machine learning models can efficiently work with large amounts of time-related data, including weather predictions, river flow rates, and past hazard data. Such models are commonly combined with decision support systems, which enable decision-makers to simulate various situations, identify vulnerable groups, and prioritize action against such responses.

The decisions of planning and allocation that are usually made over the course of months or years are related to the optimization of natural resources and the reduction of the adverse environmental consequences. Indicatively, water allocation systems have to strike a balance among competing water needs of other sectors, namely agriculture, industry, and domestic use. The problems are usually solved using optimization algorithms, such as linear programming, genetic algorithms, and simulation-based optimization. The technologies can assist the decision-makers in analyzing numerous trade-offs so that the resources can be distributed efficiently, as well as achieve a number of environmental, social, and economic objectives. Integration of machine learning models would also be applicable in anticipating the availability of future resources through climate models, past results, and new trends [50,51].

Lastly, the restoration and conservation decisions are centered on the sustainability of the ecosystems and biodiversity in the long run [52]. These are usually complicated decisions and multi-objective optimization, in which the decision-makers have to compromise between conflicting objectives, including habitat restoration, species conservation, and land-use modifications. The decision support systems in this field are based on predictive models, environmental flow models, and species distribution models, and on optimization algorithms aimed at assisting the prioritization of actions using the accessible resources and desired results. There are also other technologies, including digital twins, a virtual representation of ecosystems, which are increasingly popular in such settings, allowing decision-makers to test different scenarios in restoration and determine their long-term outcomes.

4.2. Methods with High Translational Value

The techniques applied to make environmental decisions should be suitable for the type of decision, situation, and available information to make sure that intelligent technologies will be useful in supporting such decisions. We consider in this section some of the major techniques with high translational relevance, in relation to how they are applicable in the real-world decision-making context in environmental monitoring and resource management.

The problem of machine learning (ML) has become popular in environmental decision-making, due to its capacity to find patterns in high-dimensional datasets [48]. Algorithms that are typically used to do supervised learning to solve classification problems, including land-use classification or pollution detection, when labelled training data that are labeled are present, include supervised learning algorithms like random forests (RF), support vector machines (SVM), and gradient boosting machines (GBMs). Tasks where there might be no predefined labels or ground truth use unsupervised learning algorithms (such as k-means clustering or principal component analysis (PCA). The algorithms are good at detecting hitherto unknown patterns or trends in large data sets, and thus are useful in applications like environmental monitoring in which data can be sparse or noisy.

Deep learning (DL) was successful, especially in those tasks that involve large volumes of unstructured data, e.g., image classification or remote sensing [53]. Convolutional neural networks (CNNs) are typically applied to satellite images, and in this case, they can automatically identify changes in land cover, forest cover, and urban expansion. Deep learning-based techniques may be applied to time-series data, like temperature or pollution data, as well as to forecast future outcomes based on the historical patterns in environmental monitoring. Further developed architectures, like transformers and recurrent neural networks, can take into account sequential and time-related data and, therefore, are most suitable when it comes to predicting activities, such as weather prediction or flood modeling.

Methods of causal inference are also making their way into the environmental decision-making process that facilitates decision-makers to be knowledgeable of the causation of observed environmental changes as well as to influence policy decisions [54]. The approaches of instrumental variable regression, propensity score matching, and causal graphical models can allow decision-makers to estimate the causal relationships between environmental variables and results (e.g., the effect of land-use changes on biodiversity or the effect of water allocation policies on agricultural yields). Such techniques are especially useful in solving multi-factor problems that are complex and whose relationships between variables are not obvious and in making decisions that attempt to treat the underlying causes instead of the symptoms.

Resource allocation problems are solved using optimization techniques such as linear and nonlinear programming, where the decision-makers have to optimize among several and sometimes contradicting objectives. An example is the optimization of the use of water resources in various sectors that must be done, taking into account the availability of water, demand, and environmental flows. On the same note, multi-objective optimization will be useful in assisting the decision-makers in operations of trade-offs between various objectives, like minimizing the emission of greenhouse gases and ensuring energy security. With optimization methods, machine learning models can be combined with optimization techniques to enhance future resource availability or environmental conditions predictions to make optimization results more accurate and reliable [55,56].

4.3. Evaluation Aligned with Decisions (Not Just Accuracy)

Although predictive accuracy is a large concern in the creation of intelligent technologies, it is not necessarily the most crucial aspect as far as real-world decision-making is concerned. When making decisions in an environmental context, decision-makers must have models that not only give realistic predictions but also give insight into how uncertain and robust these predictions are [11]. It implies that the analysis of intelligent technologies should go beyond conventional accuracy levels to incorporate the criteria that will be consistent with the requirements of the decision-makers. Since environmental choices are sensitive to risk tolerance, accountability, and operational constraints, the evaluation should go beyond predictive accuracy; **Table 2** lists decision-balanced evaluation criteria and explains why each one is relevant in practice.

Table 2. Decision-aligned evaluation criteria for intelligent technologies in environmental monitoring and resource management, with rationale linked to operational and governance needs.

Evaluation Criterion	Description	Relevance for Environmental Decision-Making
Prediction Accuracy	How well the model predicts outcomes based on historical data	Crucial for operational decisions but not sufficient by itself—accuracy alone does not guarantee actionable decisions.
Uncertainty Quantification	Estimating the range of possible outcomes and their probabilities	Essential for decision-makers to assess risk and guide decisions under uncertainty (e.g., flood forecasting).
Robustness	The model's ability to maintain accuracy across different scenarios	Ensures that models remain reliable under changing conditions (e.g., climate variability or new data).
Interpretability and Transparency	The ease with which stakeholders can understand model outputs and decision rationale	Ensures decision-makers can trust and effectively use model outputs, particularly in regulatory or policy contexts.
Scalability	The ability of the technology to handle large datasets or operate at a regional or global scale	Important for models deployed across large or diverse geographic areas (e.g., satellite-based monitoring).

The possibility to measure and express uncertainty is one of the crucial features of evaluation. Environmental systems are also uncertain, and models that fail to estimate the level of uncertainty can cause overconfident predictions that can lead to poor decision-making. The quantification of uncertainty, which may include Monte Carlo simulations, Bayesian inferences, and ensemble modeling, could be useful to give a set of possible possibilities to the decision-makers with a probability attached to each one. It will enable making more informed decisions because decision-makers will be able to evaluate the risks and advantages of various actions according to the level of uncertainty of the models [57].

Besides uncertainty, the strength of a model is another important issue in its analysis. The environmental systems are dynamic, and they can change either through natural variability, climate changes or through changes in human behavior. Models that are successful in a given environment might fail when the system experiences a transformation and hence make poor decisions. Robustness testing is the testing of the effectiveness of a model in various conditions (or conditions of change), including input data variability, model parameter variability, or environmental variability. Sensitivity analysis, adversarial testing, and stress testing are some of the techniques that can be used to determine the stability of models and their resistance to changing conditions [58].

Lastly, models should be assessed for their utility in decision-making [59]. This involves the evaluation of the level of integration of models with the current decision processes, the ease with which stakeholders can read the outputs of the models, and the feasibility of the recommendations. DSS should be structured in a way that it offers clear, relevant, and timely information to decision-makers that can be directly implemented in the decision-making process regarding policy or operations. This will need easy-to-use interfaces, live-data integration, and decision support tools that assist stakeholders in facing complicated trade-offs and making informed decisions.

4.4. Deployment Patterns

The practical constraints and operational requirements of decision-makers are needed to successfully implement intelligent technologies in environmental decision-making. Patterns of deployment differ considerably based on the kind of technology, data present, and the decision scenario. As an illustration, cloud-based technologies and other technologies based on massive data processing will perhaps be more applicable to strategic decision-making, which entails long-term forecasting with massive data volumes. By comparison, edge computing technologies, where data is processed locally and in real time, are more appropriate for operational decisions, including pollution monitoring or disaster response [60].

The implementation of smart technologies should also be done based on the limitations of the physical and institutional environments [61]. In other areas, the lack of internet connection or an electricity line can pose a challenge to implementing cloud systems, which will require more localized solutions. Also, the successful implementation of new technologies can be affected by the institutional, technical, and organizational. The capacity building, training, and continuous support are critical in making sure that decision makers can properly apply intelligent technologies in order to support their decisions.

Finally, to be successful in the integration of intelligent technologies into environmental decision-making, it is necessary to attentively match the data, models, and decision requirements [9]. Mapping these technologies to targeted decision-making paths, making sure that they are discussed as per decision-relevant parameters, and resolving the limitations of deploying the intelligent systems, the latter can become a potent instrument of promoting sustainability and enhancing the efficiency of resource utilization.

5. Evidence of Impact, Risks, and Responsible Implementation

There is no use denying that intelligent technologies have the potential to improve monitoring the environment and the utilization of resources; however, to be effective in their implementation, more complex models and algorithms are needed [62]. Such technologies should not only be judged based on their predictive accuracy but also on their applicability to the real world, their ability to withstand operational pressures, and their ability to address equity and governance issues. The success of these technologies is largely determined by the closeness of their incorporation into the existing decision-making systems, the degree to which they help achieve sustainability, and the possibility of involving various stakeholders. Besides, the introduction of intelligent systems should be carried out in a responsible manner with special attention to the ethical, social, and environmental impacts. This part will explore the impact of evidence of real-life application, the risks involved in the application of these technologies, and the major principles of how such technologies can be implemented responsibly.

5.1. What Counts as "Impact" and How to Measure It

The role of intelligent technologies is more than the functionality of single models or algorithms in the environment of making environmental decisions [9,63]. An effective implementation of these technologies should yield real, quantifiable benefits to the environmental results. The effect of impact can be determined regarding both indirect and direct effects on the environment, the economy, and society. To use the example, when a machine learning model is installed to predict a wildfire, the emergency responders could identify and stop a wildfire in less time, resulting in the loss of fewer properties and less harm to the environment. In the same vein, a water optimization tool could lead to better utilization of water resources that will lessen the pressure on freshwater ecosystems and guarantee a fairer distribution of water resources in case of a drought.

The direct environmental impact is commonly quantified in terms of a reduction in emissions, a rise in the quality of water, a rise in biodiversity, or improvements in the services provided by the ecosystem [64]. As an illustration, in the sphere of pollution control, the implementation of air quality monitoring systems in real-time with predictive models could result in more reliable predictions of pollution outbreaks that allow taking necessary measures in time and minimizing health hazards to the population. The efficiency of such technologies might be estimated by the decrease in the pollutant levels or hospitalizations because of respiratory problems.

The indirect effects may be harder to measure, but still, they are significant. These are governance, stakeholder engagement, and policy design. To illustrate this, an example of a decision support system that gives clear evidence-based advice on land-use planning could result in more sustainable processes of urban development, with emphasis on green areas and minimization of the urban heat island effect. In the same manner, the participation of local communities in participatory sensing projects may increase the awareness of people and increase their environmental stewardship [65].

The effect of intelligent technologies can be measured by the holistic assessment framework, which will entail the consideration of quantitative (e.g., pollution reduction, resource savings) and qualitative (e.g., stakeholder satisfaction, trust, and transparency) aspects [66]. In addition, such an evaluation should be done at several time scales because the entire benefits of these technologies may not be recorded immediately but can be gained over months or years. To establish the links between methods and results, **Table 3** summarizes the situations of representative cases, technologies that have been employed, the decision function that is fulfilled, and key implementation lessons that form the impact. In order to base the decision-focused framework on a tangible pathway, **Figure 3** depicts an exemplary workflow of the water resource decision-making of drought periods based on monitoring inputs, forecasts, allocation, and evaluation.

Table 3. Representative applications of intelligent technologies in environmental management, linking decision context, technology choices, and reported outcomes.

Case Study	Technology Used	Decision Type	Outcome	Lessons Learned
Wildfire Detection in California	Machine learning (RNN, LSTM), satellite imagery	Early Warning & Resilience	Reduced response time to wildfires, minimized property damage	Real-time data integration is crucial for time-sensitive decisions.
Water Allocation in California	Optimization algorithms, simulation-based models	Resource Allocation & Planning	Improved efficiency in water distribution during drought periods	Multi-objective optimization can balance competing needs effectively.
Biodiversity Conservation in the Amazon	Species distribution models, digital twins	Conservation & Restoration	Prioritized conservation efforts, improved land use planning	Local community involvement enhances the relevance and acceptance of solutions.
Air Quality Monitoring in New Delhi	Real-time sensor networks, predictive models	Compliance & Enforcement	Improved air quality forecasting, reduction in pollution episodes	Continuous monitoring systems must account for real-time updates and errors in sensor data.

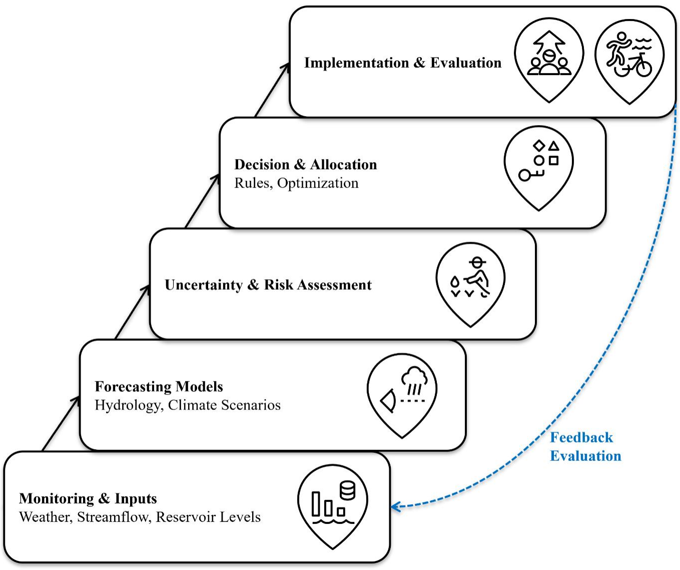

Figure 3. Illustrative decision pathway for water resource management: Monitoring and forecasting inputs, model outputs with uncertainty, allocation/constraint handling, implementation actions, and feedback evaluation.

5.2. Lessons from Real Deployments

Already, the implementation of smart technologies related to the environment has brought many useful lessons [67]. These lessons indicate the facilitators of success and the obstacles to successful implementation. The integration of smart technologies into the current decision-making processes is one of the important facilitators. New systems will be embraced and used efficiently when they are crafted to be supplementary to the already existing systems and not disruptive. Indicatively, water management agencies that have incorporated the use of optimization algorithms in daily decision-making on resource allocation have realized efficiency and fairer allocation of water, especially during peak times of scarcity. Such technologies can help decision-makers to better balance competing needs so that agricultural, industrial, and residential needs are satisfied without overwhelming proliferating ecosystems.

The other enabler is the inclusion of the stakeholders at the initial stages [68]. The effective implementations usually lead to the cooperation of the researchers, decision-makers, and the local communities. In addition to making sure that the technologies are responding to real-life issues, this participatory approach assists in instilling the trust of the stakeholders. To illustrate, in conservation of biodiversity, the use of citizen science programs where local communities are involved in the collection of data has resulted in improved coverage of data, especially where remote or under-sampled. Such programs have also heightened the awareness of the people on the environmental problems and encouraged the feeling of ownership and responsibility towards conservation actions.

On the other hand, the introduction of smart technologies has faced a number of challenges [69,70]. One of the most important obstacles is the difference between model development and reality. A large number of models do well with controlled environments and fail to deal with the complexity and variability of actual data. In practice, machine learning models trained using past climatic information might fail to work in the future with new climate conditions. In the case of this challenge, mechanisms of model adaptation and continuous learning should be integrated. This may involve online learning methods where the models can be updated in real time as new data becomes available, and also by using a group of models to model uncertainty and variability.

The second challenge is that data is not interoperable and standardized [71]. Environmental monitoring systems can be commonly used to produce data that is of a variety of kinds and is contained in various sources, which may not be easily integrated and analyzed as a whole. To eliminate this challenge, it is necessary to adopt common data standards and interoperability protocols that will allow uninterrupted integration of data across systems. Furthermore, it is of fundamental importance to make sure that data are well-documented, have clear provenance and metadata, to make sure that they can be trusted and utilized in making effective decisions.

The third difficulty is the financial and technical limitations of most organizations, especially in the low-resource environment [72]. Thoughtful technologies can be costly initially to install infrastructural support, educate, and to maintain. In low-resource areas, technical knowledge and financial resources might be inadequate to facilitate the continuity and maintenance of such systems. Consequently, it is important that local capacity is developed by means of training, transfer of knowledge, and application of low-cost and scalable technologies, which are critical in making certain that these systems become sustainable in the long term. The recurrent points of friction and success factors identified through deployments have been used to determine whether tools will continue to be used after pilots; **Table 4** summarizes the most frequently identified barriers and the factors that allow these barriers to be overcome.

Table 4. Key barriers and enabling conditions shaping the successful deployment of intelligent technologies in environmental decision-making.

Barrier	Description	Enabler	Description
Data Quality and Interoperability	Heterogeneity in data sources and formats can make integration difficult	Standardization and interoperability protocols	Data sharing frameworks and common standards improve model integration and use.
Technical and Financial Constraints	Limited resources for infrastructure, training, and ongoing model maintenance	Scalable, cost-effective solutions (e.g., cloud-based, edge computing)	Use of low-cost technologies or cloud solutions can reduce upfront costs.
Lack of Stakeholder Engagement	Poor involvement of relevant stakeholders in system design	Participatory approaches and stakeholder inclusion	Engaging communities and decision-makers from the start increases trust and relevance.
Model Adaptation to Changing Conditions	Models trained on historical data may fail under future scenarios	Online learning and continuous model updating	Adaptive learning systems that can integrate new data and evolve.

5.3. Risk, Uncertainty, and Accountability

There are various risks that come with employing intelligent technologies in the process of making environmental decisions, and these should be addressed diligently [9,73]. Among the major risks, there is the probability of decision-makers relying excessively on models and algorithms, particularly when perceived as objective or authoritative. Environmental systems are unpredictable in nature, and models are not limited to errors in data, assumptions, and predictions. The decision-makers need to be capable of interpreting uncertainties in the outputs of these models and apply such information in making their decision. Monte Carlo simulations, Bayesian methods, and ensemble techniques are some of the uncertainty quantification methods that can be used to estimate the spectrum of potential outcomes and make decisions under uncertainty.

The bias in the data or models is another risk [74]. Environmental monitoring systems are not neutral, and this implies that they represent the priorities, values, and constraints of the systems that produce them. As an example, remote sensing data can be skewed to a specific geographic region, or a citizen science project can be biased towards a specific group or region. These biases need to be detected and resolved so that intelligent technologies can be applied fairly, equitably, and inclusively. The openness of the process of gathering data, processing, and analyzing is the key to guaranteeing the trust of all stakeholders in the systems employed.

Another problem that is important is accountability [75]. Whenever intelligent technologies are employed to make decisions that involve heavy social, economic, or environmental consequences, it is critical that there are mechanisms of holding decision-makers to account for the consequences. This involves the existence of clear lines of responsibility in the decision-making process, the use of data, and model validation. It should also be in the form of decision support systems that have an audit trail enabling stakeholders to understand how they arrived at their decision, the data that were used, and the assumptions that were made behind the model outputs. This openness means that decisions are subject to scrutiny, challenge, and even betterment.

5.4. Equity, Ethics, and Justice

Equity, ethics, and justice should also dictate the use of intelligent technologies [76]. The marginalized communities are often the ones who are disproportionately affected by environmental decision-making, and biased or poorly constructed technologies can increase these effects. To illustrate, air quality surveillance systems clumped in more affluent, urbanized places will not measure pollution rates in lower-income communities or the countryside, thus not ensuring fair health conditions. It is essential to make sure that the implementation of intelligent technologies is done in a manner that focuses on environmental justice in order to establish the production of trustworthy results of equitable sustainability.

Moreover, the features of environmental monitoring systems that make use of personal information (like the data gathered by mobile applications or wearable technology) create significant privacy and consent questions. The users must be able to manage information about their use as well as be fully aware of the risks and benefits of joining such monitoring systems. There should be ethical guidelines in the collection, use, and sharing of data, which will guarantee the protection of the rights of the people, as well as ensure the acquisition of useful environmental information [77].

Moreover, the inclusion of local communities in designing and implementing intelligent technologies could assist in setting such technologies in accordance with the local needs, values, and priorities. Such participatory strategies, where the community takes part in decision-making processes, may result in more constructive and fairer results, and also may result in a better perception of ownership and responsibility of the technologies implemented [17,78].

5.5. Responsible Implementation Playbook

Introduction of intelligent technologies is a complex task that should be carried out responsibly and consider technical, social, ethical, and governance aspects [79]. Some of these principles of responsible implementation are to be transparent in model development and data collection, consider biases in data and algorithms, offer clear accountability mechanisms, and be equitable and just in the implementation of these systems. Also, it needs to continue supporting the establishment of capacity locally, the sustainability of such technologies, and engage the stakeholders in the process.

Best practices in dealing with stakeholders, requirements of making sure the decision-making processes are transparent and accountable, and risk and uncertainty management measures should be incorporated in a responsible implementation playbook [47]. It must also underscore the need to view evaluation and feedback as an ongoing process in order to make sure that intelligent technologies are producing the required results and are utilized in a manner that both beneficially affects the environment and society.

Finally, it is not only the responsible introduction of intelligent technologies but also guarantees that these tools are used in ways that facilitate sustainable, fair, and environmentally friendly effects [76,80]. It is possible to make intelligent technologies a potent force of positive change in managing the environment and distributing resources by being cautious about risks, eliminating biases, and engaging stakeholders in decision-making.

6. Conclusions

The implementation of smart technologies in environmental control and resource management is an essential step in the context of dealing with the increasingly complex nature of sustainability issues. The possibilities of these technologies to improve the decision-making process are enormous, as evidenced by air quality and water resources management, biodiversity conservation, and disaster response. The availability of data and advanced models, however, is not sufficient, as shown throughout this review. Smart technologies should be properly translated into actionable, transparent, and accountable decision support tools so that they can be used in the real-life operational environment.

The process between uncooked environmental data and informed, sustainable decisions is not straightforward. It entails addressing various technical, institutional, and social hurdles such as data quality, uncertainty, model bias, and the multiplicity of interests of the stakeholders. As we have explained, the effectiveness of intelligent systems in environmental applications is not only reliant on the predictive accuracy but also on whether they assist in decision-making in a manner that is sensitive to society, laws, and equity. The systems need to be built in such a way that they are transparent, robust, and flexible to adapt to a changing environment and arising risks.

The experiences of the actual workings of intelligent technologies in real-life environments can offer valuable insight into what works and what does not. Though success stories have been witnessed (e.g., optimization algorithms have led to better resource allocation, predictive models have enabled faster response to disasters, and real-time data have helped in environmental monitoring), the challenges persist. These are problems in the interoperability of data, the necessity of constant models, the inclusion of different stakeholders, and financial and technical obstacles to the implementation. To address these issues, it is evident that a systems-level approach is required, an approach that should consider not only the technical capacity of the intelligent technologies but also the wider governance, ethical, and social aspects of their application.

In a distant future, the way forward will be further research, development, and cooperation between scientists, policymakers, industry stakeholders, and communities. One of the priorities is the development of standardized evaluation systems and defining best practices related to the development of models, the sharing of data, and the implementation of the decision support system. Also, the local capacity-building and inclusion, and participatory processes will make sure that these technologies are implemented in both effective and equitable ways.

The potential of intelligent technologies in monitoring the environment and managing resources is crucial. With the emphasis on the combination of smart data and the transformation of intelligent systems into decision-making processes and the implementation of responsible approaches, these technologies can contribute to meaningful and sustainable results in a variety of environmental issues. Nonetheless, to ensure that they live up to their potential, it will be necessary to mount a concerted effort to counter the loopholes in governance, accountability, and equity that continue to work against their extensive adoption. When intelligently and responsibly deployed, smart technologies can be leveraged into effective instruments for meeting the global sustainability agenda that is so desirably lacking in the backdrop of climate change, biodiversity depreciation, and other increasing burdens on resources.

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