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A Framework for Monitoring the Effectiveness of Ecosystem-Based Adaptation Strategies Using Internet of Things and Machine Learning Techniques

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ABSTRACT

Climate change poses a threat to the global ecosystem. Many countries adopt various approaches, including ecosystem-based adaptation (EbA), to address this problem. However, the assessment of the effectiveness of the EbA interventions is conducted manually, is resource-intensive, and is focused on short-term outputs. These limitations underscore a critical gap: the need for a comprehensive, automated system that enables long-term monitoring and predictive analysis. This study aimed to address this gap by developing an innovative framework that integrates Internet of Things (IoT) devices and machine learning (ML) algorithms to continuously monitor weather, hydrological, environmental, and other variables. We conducted a thorough analysis to design an appropriate framework. In addition, to obtain the relevant information and

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data, we conducted interviews with the local community and collected secondary data from various sources. The proposed framework consists of five layers: (i) EbA interventions; (ii) IoT-based key performance indicators (KPI) for monitoring and evaluation (M&E); (iii) primary data collection; (iv) data storage; and (v) application. As a proof of concept, we developed a system that supports early flood and drought alerts while simultaneously providing long-term evaluations of the effectiveness of EbA strategies. The developed system consists of IoT devices and a web application integrated with machine learning (ML). We set up and tested the IoT devices before deploying them in the study area. The devices capture data for two primary purposes: (1) short-term: flood detection and alerting, and (2) long-term: drought prediction and evaluation of EbA effectiveness through continuous data analysis. This research represents a significant advancement in the automation and long-term assessment of climate adaptation measures, offering a scalable and effective solution to disaster risk reduction.

Keywords: EbA; Flood; Drought; IoT; Weather monitoring; Machine learning; KPI

1. Introduction

Climate change is a very big threat worldwide. Year by year, the impacts of climate change continue to escalate, encompassing agro-economy, natural disasters like floods, droughts, landslides, and more [1–4]. The causes of climate change vary between urban and rural settings. In urban areas, key drivers include the burning of fossil fuels, industrial processes, transportation, and rapid population growth [5–7]. In rural areas, deforestation, land use changes, agricultural practices, and energy consumption are the main contributors [5, 8–11]. Ecosystem degradation can exacerbate the frequency and severity of both floods and droughts through various mechanisms that disrupt the natural hydrological cycle and reduce the resilience of landscapes to extreme weather events [4, 12–15]. Restoration of degraded ecosystems through nature-based solutions such as forests, grasslands, and wetlands enhances carbon sequestration and improves ecosystem services such as water purification, flood regulation, and soil fertility [10, 16–23]. An approach utilized to mitigate the adverse impact of climate change on people through nature-based solutions is known as EbA [11, 24].

EbA strategies have been widely recognized as effective in reducing the risks associated with climate change-induced disasters like floods and droughts [25]. Restoration of degraded ecosystems such as forests, grasslands, and wetlands can play a critical role in reducing the risks of those disasters by retaining rainwater and increasing the soil moisture content, which will reduce the severity of the droughts [3, 12, 26, 27]. Therefore, nature-based solutions act as natural barriers against floods by capturing rain water, lowering surface runoff, and controlling water flow, then reducing the risk of flash floods and downstream inundation [13, 19, 28–31]. By enhancing biodiversity and ecosystem services, EbA approaches help communities to build resilience to both droughts and floods [14, 23, 26].

In Rwanda, efforts to cope with floods and droughts include relocation of the population from high-risk to low-risk areas [32] and EbA strategies such as reforestation to reduce runoff, crop diversification, etc. The government has launched various initiatives aimed at ecosystem restoration through different projects such as Green Amayaga, the Landscape Approach to Forest Restoration and Conservation (LAFREC) project, Nyandungu Eco-tourism Park, Green Gicumbi, and the Transforming the East-ern Province through Adaptation (TREPA) project [33].

Despite the recognized benefits of EbA, there are significant challenges in monitoring and evaluating its effectiveness. These challenges are often economic, political, or social, but a critical issue lies in the methodology used for M&E [34, 35]. While some regions use robust monitoring and evaluation frameworks, many still lack systematic approaches to assess EbA interventions, leading to inconsistencies in outcomes [36]. Traditional M&E approaches often rely on output indicators, which quantify short-term successes of project activities, such as the number of hectares of restored forests. Conversely, others utilize outcome indicators to measure the effects on ecological or social systems resulting from the project, such as decreased loss of assets or mitigated impacts of climate change on crop production [37]. However, these methods are time-consuming, labor-intensive, and often fail to capture the full scope of long-term impact of EbA intervention.

M&E of each EbA projects depends on the context because each project has its own objectives and needs. For instance, as per [38], four steps that were recommended for designing and implementing a comprehensive M&E system are (i) developing a results framework, (ii) defining indicators and establishing a baseline, (iii) implementing the monitoring and evaluation system, (iv) utilizing and disseminating the results. In the first step the overall goals and outcomes of the EbA project are outlined. In the second step, specific indicators are defined as well as measurable parameters that will be used to evaluate the progress toward achieving the goals. Baseline data are set as a reference point for measuring change and progress over time [39, 40]. In the third stage, the evaluation of pivotal elements for implementing an M&E system for EbA involves selecting an appropriate evaluation framework [38]. The last stage consists of the dissemination of the findings of M&E process for the adaptive management decisions, and external stakeholders such as donors, policymakers, local communities, and broader adaptation networks [41].

Identification of the KPIs for EbA interventions can be a complex task [37]. Therefore, the articulation of adaptation outcomes achievable through EbA, alongside the identification of indicators to monitor these outcomes, holds significant importance [41, 42]. This process is essential for assessing whether EbA initiatives are yielding the anticipated adaptation outcomes [43–45] and for discerning the effectiveness of various EbA interventions. Consequently, it facilitates a more targeted approach toward future EbA endeavors [46]. A wide array of EbA indicators serves different monitoring and evaluation functions. These encompass indicators for adaptation policy processes, monitoring the execution of adaptation initiatives, assessing levels of awareness, knowledge, and engagement, as well as evaluating the effectiveness and efficiency of adaptation actions, among others [47, 48].

In a broader context, indicators are typically divided into two primary categories: process-based and performance-based (or results-based) [38]. Process-based indicators provide information on the development and implementation of adaptation interventions, concentrating on input indicators (which measure the quantity, quality, and timeliness of resources invested) and output indicators (which delineate and quantify short-term outcomes) [37, 41]. Performance-based indicators evaluate the effectiveness of the adaptation approach, encompassing outcome and impact indicators. Outcome-based indicators measure the medium-term results and effectiveness of adaptation solutions, while impact indicators evaluate comprehensive, long-term changes (whether intended or unintended) that result directly or indirectly from adaptation techniques [37, 46].

Given that EbA interventions often require long-term monitoring to assess their full impact, existing methods, which frequently rely on manual data collection, are insufficient for capturing the long-term effectiveness of these projects [38]. This creates a research gap: the need for an automated, scalable system that can provide continuous, real-time monitoring and evaluation of EbA interventions. The lack of such systems impedes accurate assessments of whether these measures are delivering the intended adaptation benefits to communities.

To address these challenges, there is a growing interest in integrating emerging technologies such as IoT and Artificial Intelligence (AI) into environmental monitoring systems [49]. These technologies can automate data collection on key environmental variables such as rainfall, temperature, soil moisture, and water levels thereby reducing the workload and increasing the accuracy of long-term monitoring efforts [50]. Continuous monitoring through IoT systems offers valuable insights into the long-term effects of EbA strategies, supporting adaptive management and decision-making processes.

This study aims to address the limitations of existing M&E systems for EbA by developing an automated framework that leverages IoT technology. The goals of this study are two-fold: (1) To establish a comprehensive framework for assessing the effectiveness of EbA interventions through continuous, real-time monitoring, and (2) To develop the IoT monitoring system capable for gathering data on weather, soil, and river water level for flood detection and drought predictions. In the first objective, we proposed a framework to monitor the effectiveness of the implemented EbA techniques for improvement and planning. In the second objective, as a proof of concept, an IoT system was developed and tested to monitor various weather parameters and provide early warning to the community for disaster risk reduction purposes. This leads to the central research question of this study: How can the integration of IoT-based real-time monitoring systems enhance the long-term assessment of EbA interventions in mitigating the impacts of climate change?

While previous studies have focused on assessing the short-term success of EbA interventions through manual surveys and basic output indicators, this research advances the field by introducing an automated monitoring system that leverages IoT and AI for both real-time disaster predictions and long-term evaluation of EbA effectiveness. This approach ensures that climate change adaptation strategies are not only evaluated for their short-term success but also for their sustained impact over time.

2. Materials and methods

The methodology adopted in this study was specifically chosen to address the above-mentioned main research question. using a stepwise approach, this methodology allows for the comprehensive evaluation of EbA interventions through continuous data collection, predictive modeling, and real-time monitoring.

2.1 Study area

The research was carried out in the Eastern province, Nyagatare district, at Muvunba River, Rwanda. Muvumba River is located in the North-Eastern of Rwanda and South-West Uganda. It is part of the upper headwaters of the Nile as it is one of the major rivers of Rwanda, both in size and economic importance, with a total length of 170 km and a basin size of 3500 km2. The river takes its source at Rukomo in the Gicumbi district. This river is important to the economy as its valleys and those of its tributaries are fertile and contain major tea plantations and many other agricultural products[51].

Muvumba catchment covers three districts of Rwanda, which are Gicumbi, Gatsibo, and Nyagatare. The last is among the most areas affected by the flood along the Muvumba River. The topography of the area is not high-slope but medium-slope and low-slope. Heavy rainfall in the bordering regions such as Gicumbi and Uganda, as the source of the river Muvumba, creates erosive power in the river when it is raining due to the topography of the high mountains of Gicumbi and Uganda, causing flooding in the Karama sector along the Muvumba river, destroying crops, infrastructure, and land in the areas surrounding the river[48]. This may happen even when Nyagatare has little rainfall, as reported by residents around the Muvumba River.

2.2 Framework to evaluate the effectiveness of EbA

The process used to develop a framework for evaluating the effectiveness of EbA interventions consisted of seven stages: (i) conducting a comprehensive review of existing methodologies for monitoring and evaluating EbA, (ii) examining previous EbA interventions that have been implemented in the study area, (iii) identifying KPIs for EbA, (iv) analyzing indicators and aligning them with EbA indicators based on IoT technology, (v) selecting a specific area to be monitored, (vi) determining the method for collecting and storing data from IoT indicators for M&E purposes, and (vii) performing data analysis to assess the effectiveness of EbA.

The development of a comprehensive framework for evaluating the effectiveness of EbA interventions is essential to address the main research question. This framework provides a structured approach to assess how the integration of IoT-based monitoring can enhance the long-term evaluation of EbA interventions. By aligning conventional EbA monitoring methods with real-time IoT systems, this framework establishes the foundation for continuous assessment of impact of EbA on flood and drought mitigation, directly supporting the goal of improving ecosystem resilience to climate change.

Review of the existing EbA monitoring and evaluation techniques

To enhance our comprehension of the prevailing methodologies for evaluating the effectiveness of EbA projects, we conducted a thorough review of various papers, policies, and relevant documents to identify the current or conventional approaches used in assessing the outcomes of EbA initiatives. Additionally, we engaged project managers of EbA projects and their respective stakeholders to obtain information about the challenges of the evaluation of EbA projects.

Review of the EbA interventions in the study area

Through an extensive literature review, we identified Ecosystem-based Adaptation (EbA) interventions implemented on a broader scale and subsequently narrowed down our focus to the specific area of study. In addition to this literature review, we conducted interviews with personnel responsible for EbA projects in the study area to gain deeper insights into the ongoing interventions. These interviews provided valuable contextual information that complemented our understanding from the literature. We also reviewed various documents related to EbA policies and guidelines specific to the study area, which allowed us to align our framework with existing practices and regulatory requirements [52–55].

Identification of EbA key performance indicators

After the identification of EbA projects, we proceeded to discern the KPIs commonly used to assess the effectiveness of EbA solutions. The process started with the identification of EbA indicators from the broader set of EbA projects, followed by the identification of the KPIs for evaluating the projects within the study area. The identification of EbA KPIs is a critical component of this research as it allows for the alignment of conventional performance indicators with IoT-based real-time monitoring systems, directly supporting the research question by facilitating the continuous assessment of long-term effectiveness of EbA.

Analyzing the KPIs and potential IoT indicators

We conducted a comprehensive investigation of the conventional KPIs identified in the previous step to analyze the KPIs and explore the potential for monitoring them using IoT technology. This entails a deep analysis of the specific metrics and variables for KPIs and assessing their suitability with IoT-based monitoring systems. After that, we assessed the feasibility of mapping those KPIs to the corresponding IoT indicators. The aim was to explore the opportunities of leveraging the use of IoT to enhance the M&E of EbA initiatives through the provision of real-time insights into their effectiveness and impact.

Selection of the monitoring sites

The IoT indicators identified in the previous step were carefully selected for application in the EbA interventions implemented within the study area. Subsequently, appropriate monitoring sites were identified, taking into consideration factors such as the type of ecosystem, geographical characteristics, and other relevant parameters. These considerations were crucial for ensuring the placement of sensor nodes in locations that would yield accurate and reliable data essential for assessing the effectiveness of EbA interventions and monitoring environmental changes over time.

Data collection and storage for EbA monitoring an evaluation purpose

Following the selection of monitoring sites, the next step in the methodology involves deploying sensors for real-time monitoring of the identified indicators, as outlined in Section 2.2.4. The data collected from these sensors are stored in the cloud to facilitate periodic analysis of the effectiveness of EbA interventions. The analysis is conducted at predetermined intervals, such as annually or over longer durations. Additionally, the deployed IoT devices are used for monitoring other weather data, enabling the prediction of floods and droughts for early warning and disaster risk reduction. Therefore, the deployed IoT devices serve a dual purpose: 1) short to mid-term monitoring of floods and droughts, and 2) long-term monitoring of the effectiveness of EbA interventions..

Data analysis for EbA monitoring an evaluation purpose

The concluding step of this methodology entails the analysis of long-term data collected by IoT devices for the indicators specified in Section 2.2.4. Sensors will immediately collect data after implementing EbA interventions. All data collected for the first year (all agriculture seasons) will serve as a baseline. Afterwards, continuous monitoring and analysis will be conducted by comparing the current values of monitored variables with those of the baseline. This iterative process allows for the assessment of changes and impacts resulting from EbA interventions over time, providing valuable insights for monitoring and evaluation purposes.

2.3 Data collection

The data collection process was designed to gather high-quality, long-term datasets that are crucial for evaluating the effectiveness of EbA interventions. By incorporating historical weather data and real-time sensor data, this methodology enables the tracking of environmental changes and the impact of EbA interventions over time. This step is critical to answering the research question, as it ensures that the data needed for continuous monitoring and predictive analysis is available, allowing for accurate assessment of the role EbA in mitigating climate change impacts.

The process began with a visit to the study area, which included the farmers who use the marshland around the river. The farmers shared with the researchers the actual situation they are facing and expressed their desire to be involved in the proposed solution. As illustrated in **Figure 1**, this activity was part of the data collection process, which also included data gathering from various sources, including meteorology and water resources offices, as well as the ministry responsible for disaster management. We created a dataset of weather data from 1983 to 2021, totaling 14,975 rows, by consolidating all data from eight stations in the study area and performing preprocessing to address missing, null, and anomalous values. We used the Python environment and its data analytics libraries to determine the correlations between rainfall data from various stations and river water levels. We used the synthetic minority oversampling technique (SMOTE) for data resampling to mitigate the problem of imbalanced data within the dataset.

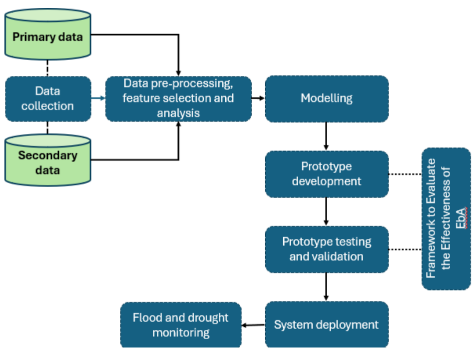

Figure 1. Methodological process.

2.4 Modelling

The training and selection of appropriate machine learning models were a crucial steps to ensure that the system could accurately predict flood and drought occurrences. This is directly linked to the central research question of the study by demonstrating the capability of IoT system to support climate change adaptation efforts through advanced data analysis and early warning systems. To determine the most suitable machine learning model (MLM) for integration into the system, we conducted training sessions with various MLMs. The selection process for models in this phase involved several criteria, such as insights obtained from literature reviews, the numerical nature of data, dataset size, and the binary classification requirement. As previously stated, different MLMs were trained; however, three were chosen based on their performance metrics: (i) logistic regression (LR), (ii) random forest (RF), and (iii) naïve bayes (NB). Other models, including artificial neural networks, support vector machine (SVM), and k-nearest neighbors (KNN), were tried but ultimately excluded due to their poor performance compared to those whose results are discussed in this study.

2.5 System design and development

The phase of system design and development plays a pivotal role in addressing the central research question by creating an IoT monitoring system capable of capturing real-time environmental data. The sensor nodes and web application are specifically designed to collect, process, and visualize data related to weather patterns, soil moisture, and river water levels, which are key indicators of flood and drought risk. This IoT-based system allows for immediate detection and response to environmental changes, directly supporting the goal of enhancing the long-term assessment of EbA interventions.

This task involved conceptualizing and constructing an IoT system consisting of a sensor nodes and a corresponding web application. As shown in **Figure 2**, the first sensor node comprises three primary components: (1) the sensing component, which is SenseCAP S700V2 7-in-1 Compact Weather Sensor; (2) the processing component, represented by the SenseCAP Sensor Hub 4G Data Logger; (3) the power source, which is the Waterproof PV-12W Solar Panel. Additionally, the sensor hub incorporates a built-in lithium rechargeable battery to provide power when solar energy is insufficient. The sensor node is linked to the 4G cellular network and subsequently to the cloud, where ML algorithms are used for predictive analysis. The second sensor node comprises only soil moisture and temperature, and water level sensors.

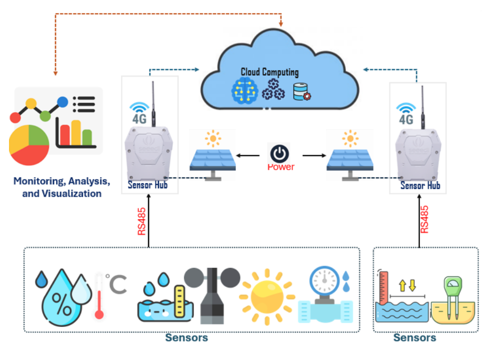

Figure 2. System Architecture.

As the sensor nodes are positioned in remote locations, their energy source comprises solar panels and rechargeable batteries integrated into each node. The system allows users to visualize data and other information on the web dashboard. This dashboard will enable communities and stakeholders to receive timely notifications of floods or droughts.

2.6 Testing and validation

To ensure the accuracy and reliability of the developed system, we used different steps. Initially, we carried out unit testing, in which we tested each system component on both hardware and software. Testing on the hardware (sensor node) consists of different sensors and their connectivity to the processing unit [56]. We also tested the integration of different hardware components to check their compatibility. The testing of hardware also comprised data validity testing, where we compared the data from our devices with those gathered by weather stations, and where necessary, the calibration was performed. After the hardware testing, the data transmission module was tested where the application programming interface (API) was developed and configured to the sensor nodes connected to the network and tested to see if the data could reach the databases. We started testing the web application by focusing on individual modules like ML-AI, prediction, alerts, monitoring, and analysis. After unit testing and confirming the functionality of each, we then conducted integration testing to evaluate the interaction and compatibility of various system components when integrated into the overall architecture. Since the accuracy of the prediction of the system in the real scenarios will take time (i.e waiting for disaster events), this test was left out and is considered for future work. However, we conducted simulations of probable flood and drought scenarios.

2.7 System deployment

After a complete test, we conducted a field visit to find the strategic locations to deploy sensor nodes, and we deployed them on the selected sites. We installed the first sensor node in an area previously identified as the source of rainfall responsible for floods, enabling real-time monitoring of crucial weather parameters, while the second sensor node was deployed along the river to monitor water levels and soil moisture and temperature in the wetland. We deployed the web application on a cloud computing service of the service provider.

2.8 Data gathering and monitoring

After system deployment, continuous monitoring of weather and hydrological data started. The real-time data from sensor nodes is transmitted to the database hosted by the cloud server, and important data can be visualized on the system dashboard. ML powers the system, enabling analytics. The system data logger saves data in the event of an Internet disruption and transmits all pending data once the Internet returns. To ensure instant notifications of data, the transmission protocol used during development is message queuing telemetry transport (MQTT), where the sensor nodes are configured as clients subscribed to topics through the E-MQTT broker. This scenario uses hypertext transfer protocol (HTTP) for user data access and management.

The continuous gathering and monitoring of data via the IoT system are key to addressing the research question. By collecting real-time data on environmental variables, the system supports the long-term assessment of EbA interventions by providing insights into their effectiveness in reducing flood and drought risks. This ongoing monitoring ensures that the system can detect changes over time, allowing for adaptive management of EbA strategies based on real-time feedback, thus contributing to improved climate change resilience.

3. Results

In this section, we present the key findings from our study, which directly address the central research question. The two main contributions of this research are: (1) the development of a framework to assess the effectiveness of EbA interventions using IoT, and (2) the implementation of an IoT-based weather and river water level monitoring system aimed at reducing the risks associated with floods and droughts. The framework to assess the effectiveness of EbA interventions using IoT provides a structured approach for evaluating the performance of EbA measures in real-time. This framework is designed to enhance the accuracy, timeliness, and long-term utility of data collected through IoT devices, enabling a more detailed understanding of how these interventions perform under varying climate conditions.

The IoT-based weather and river water level monitoring system demonstrates the practical application of IoT technologies in the context of flood and drought risk reduction. This system integrates real-time weather data and river water level measurements to improve the prediction and management of climate-related disasters, offering a critical tool for decision-makers and stakeholders involved in climate resilience efforts. These findings collectively demonstrate how IoT systems can be leveraged to enhance the long-term assessment and effectiveness of EbA interventions, ultimately contributing to better-informed strategies for mitigating the impacts of climate change. The following sections delve into the detailed results for each of these main findings.

3.1 Framework to assess the effectiveness of EbA interventions using IoT

The current evaluation of the effectiveness of EbA approaches faces several challenges. A lack of universal metrics for adaptation leads to uncertainties about what specific aspects should be monitored and which indicators should be used[57].

Actual monitoring & evaluation techniques for EbA interventions

As discussed in the introduction section, EbA indicators can be classified into two categories, process-based and results-based indicators. In this study, we focused on identifying indicators, which is one of the steps followed to conduct a results-based assessment. **Table 1** provides some of the existing EbA approaches and their respective indicators (extracted from[37, 38, 58]).

The interventions described in this table can be evaluated using quantitative indicators by setting up a baseline before implementing EbA and assessing outcomes over a medium to long-term period. These indicators include, but not limited to income derived from sustainable farming or fishing per household following extreme weather occurrences or over a period of time; assessing changes in infrastructure, residences, transportation routes, agricultural land degradation, conservation areas, erosion rates, household crop and livestock output, availability of clean water during severe events, demographic effects on health and mortality rates, levels of air pollution, and local air temperature variation before and after EbA interventions[38].

EbA interventions implemented in rwanda

The EbA approach has been used in Rwanda to rehabilitate degraded wetlands, forests, and savanna ecosystems. The most common activities are depicted in **Table 2**. Additionally, the government of Rwanda has proposed various initiatives to mitigate the impact of climate change in Nyagatare District, which faces both floods and droughts. Umuvumba Multipurpose Dam Development Project was initiated by the Ministry of Environment. The dam is being constructed on the Muvumba river to control flooding downstream of the Muvumba River by storing water in reservoirs. The project aims to enhance productivity through watershed management, water harvesting in valley dams, and hillside irrigation.

Ecosystem-based adaptation monitoring framework

The framework is shown in **Figure 3** and consists of five layers: EbA interventions, IoT-based KPIs, data collection, data storage, and application.

Layer 1—EbA interventions: At the lowest level, every intervention should be analyzed to identify potential M&E indicators. These indicators should be categorized as either quantitative or qualitative, and the possibility of incorporating IoT indicators should be explored if relevant.

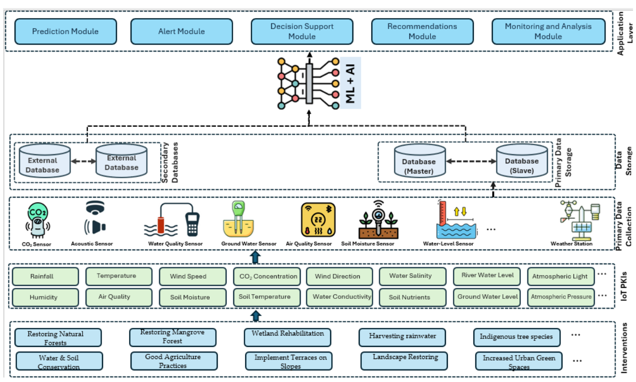

Figure 3. Framework for EbA M&E using IoT.

Layer 2—IoT KPIs layer: The second layer of the framework involves identifying KPIs for the IoT derived from the EbA interventions in the first layer. The KPIs comprise different environmental parameters that are essential for weather forecasting and early warning systems. These parameters have two main functions: (i) to predict weather in real-time and early warning of floods or droughts, (ii) to monitor and evaluating continuously the effects of EbA interven-

Table 1. Most Common EbA interventions and their evaluation indicators.

EbA interventions	Outputs	Outcomes
Wetland rehabilitation	Hectares of wetland rehabilitated	Reduction in the impact of drought on water quantity
Protection or restoration of mangroves	Plan seeking mangrove protection	Reduction in loss of lives and damages to assets in coastal communities due to storms
High-altitude forest restoration and protection	Hectares of forests restored or protected	Reduction of loss of assets of communities and infrastructure due to extreme weather events
Implementation of good agriculture practices such as agroforestry, soil conservation, and application of organic fertilizer and pesticides	Farmers implementing particular practices	Reduction in crop loss due to extreme weather events
Restoration of swamp forests and development and rehabilitation of overflow areas and reed marshes	Hectares of swamp forests restored,	Decreased effects of climate change on the prevalence of vector-borne diseases linked to extreme weather conditions such as flooding and drought
Implementing green roofs and planting trees in urban environments	Number of green roofs implemented, and number of trees planted in urban areas	Reduced negative health effects, such as respiratory issues and heat stroke, resulting from extreme temperatures and fires
Implement terraces on slopes	Hectares of slopes terraced	Reduced soil erosion on slopes, improved soil structure and fertility, better water infiltration, and enhanced water availability in the soil
Apply soil and water conservation methods	Area of land implemented with the conservation technique	Enhanced soil structure, fertility, and nutrient retention
Implement covering crops or using shade cover	Hectares of land with cover crops or shade cover implemented	Improved Soil Health and nutrient cycling, reduced weed growth, enhanced water retention, and increased crop yields
Restore degraded, flood-prone, and ecologically sensitive areas	Hectares of degraded, flood-prone, and ecologically sensitive areas restored	Improved water quality, and strengthens community resilience to climate impacts

tions over medium to long-term periods after they have been implemented. This layer ensures that IoT technologies are used to enhance both the immediate readiness for disasters and the ongoing evaluation of ecological restoration activities within the context of EbA. Examples of these parameters include, but are not limited to, rainfall, atmospheric temperature, humidity, atmospheric pressure, light, wind speed and direction, soil moisture, groundwater level, river water level, soil temperature, CO_2 concentration, water conductivity, salinity, total dissolved solids (TDS), air quality, soil nutrients, bird/insect sounds, pore water pressure, and ground movement.

Layer 3—Primary Data collection: The third layer of the framework consists of remote sensing. Each parameter that is selected from the second layer corresponds directly to the indicators identified to measure the outcomes of EbA interventions. This layer uses IoT sensors to collect data on environmental factors such as rainfall, atmospheric temperature and humidity, soil moisture, water levels (both groundwater and river), air quality, soil nutrients, and other pertinent measurements. IoT sensors are deployed in strategic areas to gather data.

Layer 4—Data storage: The fourth layer of the framework is dedicated to data storage in the cloud, consisting of two types of databases: primary and secondary. The primary database contains current data from the IoT sensors, while

Table 2. EbA activities implemented in Rwanda [52–55, 59].

Ecosystem types	Location	EbA activities									
		Agroforestry	**Bamboo contours**	**Installation of small-scale solar-powered irrigation systems**	**Harvesting rainwater**	**Removing Invasive aquatic species/weeds**	**Excavation of buffer zone demarcation/restoration trench**	**Radical terraces**	**Livestock provision to the households**	**Indigenous tree species**	**Landscape restoration**
Wetland	Kibare Lakeshores (Kayonza district)	✓	✓	✓	✓		✓				
	Murago wetland (Bugesera district)	✓	✓	✓	✓		✓				
	Lake Cyohoha North					✓					
	Rwampanga Lakeshores (Kirehe district)	✓	✓				✓				
	Nyagatare district				✓						
	Nyiramuhondi wateshed	✓	✓					✓	✓		
	Ruhondo Island (Musanze district)								✓		
	Nyandungu Urban wetland									✓	✓
Natural forest	Ibanda Makera natural forest (Kirehe district)	✓								✓	
	Sanza natural forest (Ngororero district)									✓	
	Amayaga (Kamonyi, Ruhango, Nyanza, Gisagara districts)	✓							✓		
	Rutsiro and Ngororero districts	✓					✓		✓		✓
	Gicumbi district	✓	✓		✓			✓			
	Eastern Province	✓									✓
Savannah	Rwinkwavu hill (Kayonza district)									✓	

the secondary database stores historical data from various sources. For primary data storage, we opted to use a master-slave architecture. This widely adopted database replication strategy ensures secure, scalable, and efficient storage of vast amounts of environmental data while maintaining data integrity and availability. The master database handles all write requests, while the slave databases can take over in the event of a master server failure, thereby enhancing availability and reliability. This architecture also contributes to improved security by ensuring continuous data access and reducing the risk of data loss. Secondary databases consist of data sourced from stakeholders. We recommend maintaining a synchronized copy of these data, updated at the end of each day. This setup ensures data reliability and continuity, even in the event of inaccessibility or unavailability of the stakeholder databases. Both primary and secondary data will be hosted in cloud databases, serving as a central repository organized for easy access and retrieval. These databases support real-time data processing, historical data analysis, and integration with other data sources. The data is made available to various modules in the application layer, facilitating diverse analytical and reporting functionalities.

Layer 5—Application: The uppermost layer of the architecture comprises the application layer, comprising different modules created specially to make use of the stored data for comprehensive monitoring, assessment, and decision support. These modules are operated by an AI system that applies ML algorithms and accesses both primary and secondary.

1. *Prediction Module:* This module applies ML algorithms to analyze historical and current data, predicting climate-related hazards and ecosystem responses. Through the analysis of extensive data, it can forecast occurrences such as floods, droughts, variations in vegetation health, and changes in water quality. These forecasts provide pre-emptive planning and adaptation actions to minimize potential effects on ecosystems and populations.
2. *Alert Module:* The alert module uses AI to continually monitor data inputs and identify anomalies or exceedances of thresholds. When anticipated dangers or particular thresholds are surpassed, it activates automatic alerts and notifications to relevant parties. This allows for crucial advance notice to be taken for the purpose of readiness and reaction measures. Alerts can be tailored according to their category (such as flood warning or drought alert), frequency, and intended recipient (such as local authorities, farmers, or community members) to guarantee efficient and prompt communication.
3. *Decision Support Module:* This module utilizes AI to provide decision-makers data-driven insights and alternatives for efficient ecosystem management and adaption techniques. It integrates predictive analytics, impact analysis, and cost-benefit evaluations to assist in making well-informed decisions. By providing a range of possible situations and their potential impacts, it assists stakeholders in selecting the most effective strategies to enhance the ability of the ecosystem to withstand disturbances and promote community welfare.
4. *Recommendation Module:* This module is used to make customized recommendations for EbA interventions. Through an analysis of projected results, past data, and assessments of costs and benefits, it provides specific suggestions for conservation actions, infrastructure funding, or policy modifications. These recommendations aim at improving the ability of ecosystems to withstand and recover from disturbances, while also ensuring long-term viability. They provide guidance to stakeholders on how to efficiently implement strategies for adapting to changing conditions.
5. *Monitoring and Analysis Module:* This module applies AI to combine data from many sources, such as IoT sensors, databases, and stakeholder feedback. The system consistently monitors and assesses the efficiency of EbA initiatives, offering valuable information for enhancement and adaptive management. By identifying patterns and evaluating success, it facilitates continuous improvement of EbA initiatives and provides valuable insights for future decision-making.

The combination of these AI-enabled modules creates a robust framework for monitoring, assessing, and overseeing EbA measures. This system leverages IoT technology to improve the ability to withstand and maintain sustainability in response to climate change.

Indicators to track the effectiveness of EbA interventions Top of Form

Evaluating the success of EbA interventions can be enhanced using IoT for certain interventions, while for others it may not be feasible. **Table 3** below highlights various interventions along with potential IoT parameters and sensors that can be utilized to monitor the effectiveness of these interventions.

Bottom of Form

The identification of specific IoT indicators and sensors for monitoring the effectiveness of EbA interventions provides a practical framework for both research and application. This framework contributes to a deeper understanding of how diverse ecosystem services can be quantitatively assessed using IoT technologies, fostering further exploration into ecosystem-based adaptation strategies. Practitioners benefit from this research by gaining actionable insights into selecting and implementing appropriate sensors for monitoring critical indicators, enabling data-driven decisions to enhance the resilience of ecosystems to climate change impacts such as floods, droughts, and land degradation.

Automated monitoring and data management for EbA interventions using IoT sensors

To implement any EbA project in a specific area, a feasibility study on the use of IoT devices to capture environmental data will be conducted, and a customized device

Table 3. Indicators and sensors to monitor effectiveness of EbA interventions.

EbA Intervention	Ecosystem service	IoT indicators	Potential sensors
Restoring natural forests and vegetation	Controls soil erosion, conserves water, maintains soil nutrients, increases productivity, reduces landslide and flood risks, and enhances cloud formation and rainfall.	Soil moisture, soil temperature, soil nutrients, erosion rates, rainfall, groundwater levels, river water levels, vegetation health, air quality, temperature and humidity, biodiversity indicators	Soil moisture sensor, soil temperature sensor, soil nutrient sensor, erosion sensor, rainfall gauge, groundwater level sensor, water level sensor, normalized difference vegetation index (NDVI) sensor, air quality sensor, temperature and humidity sensor, acoustic sensor
Water conservation	Enhanced water availability, improved water quality, groundwater recharge, soil moisture retention, erosion control, climate regulation, biodiversity support, flood mitigation, drought resilience	Soil moisture, precipitation, groundwater levels, surface water level, soil temperature, water quality, atmospheric humidity, air temperature, water temperature, soil salinity, water salinity, evapotranspiration rate	Soil moisture sensor, rainfall gauge, groundwater level sensor, water level sensor, soil temperature sensor, water quality sensors, humidity sensors, temperature sensor, salinity sensor, evapotranspiration sensor
Agroecology and diversification	Improves soil fertility, reduces erosion, and natural pest control can reduce	Soil moisture levels, soil nutrient levels, soil temperature, crop health and vegetation index, rainfall, air temperature and humidity, pollination activity, carbon dioxide (CO_2) concentration	Soil moisture sensor, soil nutrient sensor, soil temperature sensor, NDVI (normalized difference vegetation index) sensor, rainfall gauge, temperature & humidity sensor, acoustic sensor, CO_2 sensor
Restoring and conserving mangrove forest	Reducing coastal flooding, wave inundation, and land erosion	Soil moisture, soil salinity, water quality, groundwater level, surface water level, vegetation health and coverage, carbon dioxide (CO_2) concentration, air temperature and humidity, sediment accumulation rates, biodiversity indicator	Soil moisture sensor, salinity sensor, water quality sensor, groundwater level sensor, water level sensor, NDVI (normalized difference vegetation index) sensor, CO_2 sensor, temperature & humidity sensor, sediment sensor, acoustic sensor
Implementation of agriculture	Enhanced soil health, biodiversity, water retention, carbon sequestration, and sustainable crop yields.	soil moisture, soil nutrient, Soil temperature, soil erosion rates, precipitation, vegetation health and coverage, carbon dioxide (CO_2) concentration, air temperature and humidity, biodiversity indicator, evapotranspiration rates	Soil moisture sensor, soil nutrient sensor, soil temperature sensor, erosion sensor, rain gauge, NDVI sensor, CO_2 sensor, temperature & humidity sensor, acoustic sensor, evapotranspiration sensor
Restoration of swamp forest	Reduced flood risks, improved water quality, sequesters carbon, supports biodiversity, and provides recreational opportunities	Water table level, water quality, soil moisture level, vegetation health and coverage, sedimentation rates, air temperature and humidity, biodiversity indicator, carbon dioxide (CO_2) concentration, flooding frequency and duration	Groundwater level sensor, water quality sensor, soil moisture sensor, NDVI sensor, sediment sensor, temperature & humidity sensor, acoustic sensor, CO_2 sensor, water level sensor
Increasing urban green spaces and tree canopy cover	Provide shade, cool the surrounding air through evapotranspiration, and filter pollutants, thereby lowering the risk of heat-related illnesses like respiratory distress and heat stroke among urban residents	Air quality, air temperature regulation, air humidity level, evapotranspiration rates, biodiversity indicator, carbon dioxide (CO_2) concentration	Air quality sensor, temperature sensor, temperature & humidity sensor, evapotranspiration sensor, acoustic sensor, CO_2 sensor, water

with suitable sensors will be selected. Immediately after the EbA intervention is implemented, an appropriate number of devices will be deployed in the intervention area. After calibration and configuration, these devices will capture measurements and transmit them to the cloud via internetwork like cellular or long range (LoRa) networks. The data will be stored in a database that can be accessed anytime in common formats like comma-separated values (CSV). The transmission frequency for each sensor is adjusted based on the significance of the data type. For example, data such as rainfall and river water levels require frequent updates during rainfall, while others like water quality, air quality, and soil moisture do not need as frequent transmissions. The collected data, saved daily, can be used for forecasting and early warning purposes, much like a weather station. Periodical averages can be calculated daily, weekly, monthly, and annually.

After one year (all seasons) of monitoring, baselines will be set for each indicator, allowing the effectiveness of the EbA intervention to be assessed by comparing current data with previous years (seasons). As shown in Table 3, the parameters used to evaluate effectiveness of each intervention will differ. However, many IoT indicators are common, highlighting the advantage of using IoT sensors, as one sensor can monitor multiple EbA interventions. AI-powered decision support and recommendation modules can use the results of the analysis module to help people at all levels, from local communities to higher authorities, make decisions about informing the community or taking the right steps for the EbA intervention that has been implemented. The prediction and alert modules can help local people prepare for imminent disasters, such as floods or droughts, enabling timely rescue or other appropriate measures.

This automated process eliminates the need for M&E teams to manually collect and record the EbA output or outcome data, reducing errors and inconsistencies from manual data entry. The IoT devices used in this automation should be simple to maintain, featuring weather-proof protection, solar-powered autonomous operation, long battery life, and low battery alerts.

3.2 IoT-based weather and river water level monitoring system for floods and drought risk reduction

It was stated that to achieve the second objective of this study, we used IoT devices to monitor weather, soil and water level data which were integrated with ML algorithms. As mentioned in the methodology section, to identify the best MLM, we used different ML algorithms, including LR, RF, NB for comparison purposes. The results from the trained models were presented at the Mediterranean Geoscience Conference held in Istanbul in 2023 (https://2023.medgu.org) in the conference paper titled "Weather Data Analysis with Predictive Modelling for Floods in Muvumba Catchment of Rwanda," which, according to the conference organizer, will be published online in Springer before the end of 2024. **Table 4** indicates the performance of the MLMs.

From these results, we opted to integrate Naïve Bayes model with our IoT system because as discussed in our conference paper, it was the best in the FNR and recommended to be used in this study.

The developed system consisted of two IoT sensor nodes for weather monitoring and early warning of floods and droughts incidences as described in the methodology. The first sensor node captures rainfall, air temperature, air humidity, barometric pressure, wind speed, wind direction, and light intensity. The second sensor node is made of water level, soil moisture, and soil temperature sensors. As mentioned earlier, we deployed the first sensor in the area that was identified as the source of rainfall that causes floods in the area of study, and the second sensor node on the Muvumba River to monitor the variation of water levels in the river for the prediction of floods, as well as soil moisture and temperature in the wetland for drought detection or prediction. We used industrial IoT devices from SEEED Studio that comprise two main components: a sensing part (weather station/sensors) and a data logger (4G sensor hub) as shown in **Figure 4**.

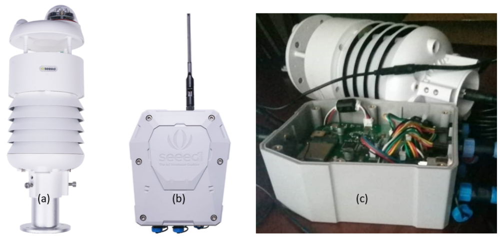

Figure 4. IoT device: (**a**) weather station , (**b**) sensor hub 4G data Logger, (**c**) device in setup and configuration process.

The GSM module inside the sensor hub allows the transmission of data from the sensor node to the cloud for storage, modelling, and prediction of floods or droughts. The current data is added to the existing database, and the accumulated data will be used as historical data in the future. This historical data will also be used for analyzing the effectiveness of the EbA intervention. **Figure 5** presents a sample of weather data captured by the sensor node for the period of five months.

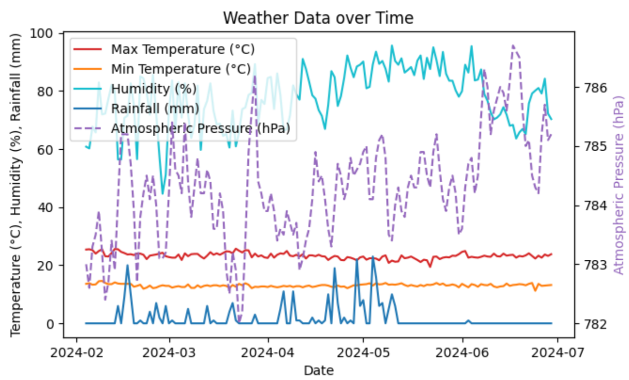

Figure 5. Weather data over time.

A web platform was also developed, which comprises different modules such as dashboard, alert module, users management and stations management modules, etc. as shown in **Figure 6**.

Table 4. MLMs Performances.

Model	TPR (%)	TNR (%)	FNR (%)	FPR (%)	Overall accuracy (%)
Logistic Regression	89.6	95.5	10.3	4.5	95.36
Random Forest	86.2	95.3	13.8	4.7	94.89
Naïve Bayes	91.4	91.9	8.6	8.1	91.92

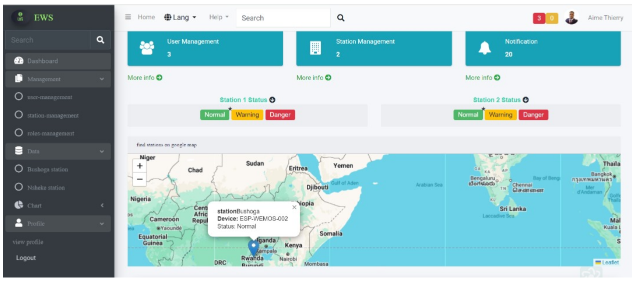

Figure 6. The system landing page.

The second objective was achieved by implementing the proposed framework as stated in the first objective. From layer 1 to layer 5, we considered interventions such as wetland rehabilitation, implementation of terraces in slope areas, and soil protection (layer 1). In layer 2, we opted to monitor weather data, river water levels, soil moisture, and temperature. These are KPIs for the IoT, and in layer 3, we installed sensor nodes to capture data for those indicators. The databases were created to host both primary and secondary data (layer 4). The web platform, developed in the application layer (layer 5), consists of various modules. One of these modules is the alert module, which can provide early warnings for disasters. Another module is the monitoring and analysis module, which provides analytical information on the effectiveness of an EbA strategy after a certain period since its implementation.

4. Discussion

Efficiency of adaptation strategies for climate change is optimized when they are customized to the unique conditions of a single area for a specific type of ecosystem. IoT sensors and weather stations play a vital role in monitoring and collecting data to inform plans during the implementation of EbA.

4.1 Usefulness of the gathered data

In the specified area of implementation, various IoT sensors will be selected and installed based on the environmental parameters that need to be monitored. Data will be collected on a daily basis in time series, with the frequency of data collection determined by the significance of the variation and impact of the parameters being monitored. This systematic approach allows the gathering of short, medium, and long-term data, which is essential for comprehensive analysis and decision-making.

Short-term predictions and alert modules during rainy events rely heavily on weather data, which are critical for timely interventions. Therefore, weather parameters can be used to provide early warnings to the local community and decision-makers, thereby enhancing disaster risk reduction efforts. Timely alerts can help mitigate the adverse effects of floods and droughts, protecting both lives and property.

Medium-term data collection involves parameters such as temperature, humidity, wind, and air pressure. These data can be used for forecasting over weeks or months, helping in agricultural planning, water resource management, and preparation for seasonal weather variations. Forecasting medium-term weather patterns can help communities adapt to changing conditions and optimize their resource use.

Long-term data collection focuses on parameters that indicate the overall effectiveness of EbA interventions. This includes all others described in **Table 3** such as those related to air quality, water quality, soil moisture, groundwater levels, and CO_2 concentration. Analyzing these indicators over an extended period of time (years) reveals trends and impacts that may not be observed for a short time (months or one year). Long-term data analysis provides valuable insights into the sustainability and success of EbA measures, informing future adaptation strategies and policy decisions.

4.2 Usefulness of the framework

The proposed framework and developed IoT system for monitoring and evaluating the effectiveness of EbA interventions are highly suitable for addressing various challenges across different domains, namely social, ecological, political, and economic areas. **Table 5** provides the advantages of

Table 5. Advantages of the proposed framework.

Area	Suitability	Impacts	
Social	Public Health and Safety	The system can forecast floods and droughts by monitoring meteorological conditions, river water levels, and soil moisture. This helps communities be better prepared and reduces an likelihood of losses caused by natural disasters.	Timely information about environmental conditions can help communities adapt their practices, ensuring better living conditions and health outcomes
	Community Engagement	Application layer of the framework contains modules for alerting and recommending actions, which facilitate prompt responses by communities to environmental changes. Engaging local stakeholders in monitoring operations can promote community involvement and education.	Providing communities with real-time data and actionable recommendations empowers them to take proactive measures to protect their environment and livelihoods.
Ecological	Biodiversity Conservation	The ability of the system to monitor various ecological parameters helps in assessing the health of ecosystems, such as wetlands, forests, and agricultural areas. This data is crucial for implementing effective conservation strategies	Effective monitoring and evaluation help maintain ecosystem services such as water purification, flood regulation, and carbon sequestration, which are vital for ecological balance.
	Restoration Efforts	The detailed data collected helps in the evaluation of restoration projects, ensuring that interventions are effective and adaptive management strategies can be employed when needed.	The framework promotes the use of IoT for continuous monitoring, encouraging the adoption of sustainable practices that preserve natural habitats and biodiversity.
Political	Policy Formulation	The robust data generated by the system provides a solid foundation for policymakers to develop evidence-based environmental policies and regulations	Policymakers can make informed decisions based on reliable data, leading to more effective and sustainable environmental governance.
	Compliance and Accountability	The capabilities of the real-time monitoring system ensure compliance with environmental laws and policies, holding stakeholders accountable for their actions.	The system fosters collaboration among different governmental and non-governmental organizations by providing a common platform for data sharing and analysis.
Economic	Resource Management	By providing insights into the effectiveness of EbA interventions, the system aids in the efficient allocation of resources, ensuring that investments in adaptation measures yield maximum benefits	Early detection and response to environmental threats can significantly reduce the costs associated with disaster recovery and management.
	Risk Mitigation	Predicting and mitigating the impacts of environmental disasters helps protect infrastructure and reduces economic losses, supporting sustainable economic growth	The system supports the resilience of local economies by safeguarding agricultural productivity and protecting natural resources that communities rely on for their livelihoods

using this framework.

The proposed framework offers immense value to both academic researchers and practitioners working in the fields of climate adaptation, disaster risk management, and environmental conservation. For academics, this framework provides a multidisciplinary tool for investigating how IoT-based monitoring systems can enhance the understanding of complex ecosystem dynamics, social behaviors, and policy outcomes. For practitioners, the framework provides actionable, real-time insights across social, ecological, political, and economic domains. This facilitates better-informed decisions that lead to more efficient resource management, proactive disaster risk mitigation, and improved community engagement. Its versatility ensures that policymakers, conservationists, and local communities can adapt and respond to environmental changes effectively, fostering resilience and long-term sustainability.

4.3 The use of weather stations for early warning of disasters

Weather stations are used to collect meteorological data, provide weather forecasts, and provide predictions. In some countries they can also be used to provide warning notifications of weather-related disasters [60]. These solutions have the potential to significantly reduce risks or disaster impacts. However, the distribution or coverage of weather stations is a challenge, as existing stations are frequently inadequate to thoroughly monitor and cover entire regions. So, to monitor the effectiveness of EbA solutions, it is important to do strategic studies and analyses to figure out what devices are needed for different areas that need to be monitored like specific catchments or areas where EbA interventions are being implemented. Sufficient IoT devices need to be identified and deployed to ensure accurate, reliable data and a robust system. For instance, effective flood monitoring on downstream rivers requires the monitoring of river water levels from all upstream tributaries, as well as rainfall monitoring across the entire catchment.

The integration of weather stations and IoT-based monitoring systems offers significant contributions to both academic research and practical applications in disaster risk reduction and environmental management. For academics, these systems provide a rich source of data that can be utilized for modeling and predicting climate-induced disasters, enhancing our understanding of climate patterns, and advancing the study of EbA solutions. This contributes to the development of more accurate predictive models and resilience-building strategies. For practitioners, especially those involved in disaster management and climate adaptation, this section underscores the importance of the strategic deployment of weather stations and IoT devices. By ensuring comprehensive coverage in areas vulnerable to climate-induced hazards, practitioners can improve early warning systems, enhance real-time decision-making, and minimize the impacts of floods and droughts on communities and ecosystems.

4.4 Implications for broader contexts

In the proposed framework, we recommend the use existing weather stations, enhancing them with customized IoT devices to collect additional data. This strategy is economically efficient because it enables the collection of data over an extended period of time, in contrast to conventional methods (such as conducting surveys) of M&E for EbA interventions. Although this study was conducted in regions with specific climatic conditions, the modular nature of the IoT framework allows for adaptation to different ecosystems and hazard types.

The novelty of this framework lies in its capacity to adapt to varying ecosystems and hazard types, making it highly versatile for climate adaptation strategies across diverse environments. Unlike traditional monitoring methods, the integration of IoT devices with existing weather stations facilitates continuous, real-time data collection, leading to more accurate and timely decision-making. This approach not only enhances the long-term assessment of EbA interventions but also provides a scalable solution that can be customized for different regions. The contribution to new knowledge is evident in how this system bridges the gap between academic research and practical application. By enabling predictive modeling based on real-time environmental data, the framework supports more precise disaster risk reduction strategies and fosters resilience across ecosystems, providing a foundation for future research in other challenging contexts like coastal and arid regions.

4.5 Threats to validity

In this section, we discuss some threats to the validity of our study. We categorize them into two categories: construct validity and internal validity.

Construct validity

Construct validity relates to sources investigated and data collection. To address construct validity, we recognize that the EbA activities, interventions, and indicators included in this study are not exhaustive. We only included the common ones identified in the literature, and it is possible that other relevant elements may exist. To mitigate this threat, we collaborated with REMA and consulted various project implementation reports to ensure no significant activities, interventions, or indicators were overlooked. Additionally, we believe our proposed framework is flexible enough to incorporate additional elements when identified.

Internal validity

The selection of Naïve Bayes poses a potential threat to the validity of our study. Our choice was based on its superior performance, particularly regarding the FNR. However, we acknowledge that other classifiers might also yield good results. Additionally, the validation of our findings presents another threat. Despite our efforts to secure validation sessions with Meteorology office in Rwanda or access real-time data through their API, we did not receive a response because of some legal constraints, such as having no memorandum of understanding in the context of this research. Nonetheless, we consider this threat acceptable since the results presented in our developed prototype are based on real data captured by actual sensors, and we plan to have validation in our future work. Additionally, evaluating the performance of the system and the effectiveness of EbA interventions will require several years of data collection. This is necessary to capture enough data from sensors and to monitor flood and drought events comprehensively.

5. Conclusions

We presented a comprehensive framework for assessing the effectiveness of EbA strategies and developed a weather and hydrological variable monitoring system that enables early flood and drought alerts. We started by conducting interviews with the practitioners of EbA interventions to identify the implemented EbA projects and how they are currently evaluated. We further conducted interviews with the local community to collect relevant information and data from various sources. We used the information from the literature review and interviews to develop the proposed framework.

The proposed framework consists of five layers: (i) EbA interventions, (ii) IoT indicators for M&E, (iii) Primary data collection, (iv) Data storage, (v) Application. Finally, we developed a proof of concept tool for continuous monitoring of weather and hydrological variables, integrating IoT devices with ML algorithm to provide long-term performance evaluations of EbA strategies together with rapid disaster warnings. We deployed IoT devices to capture data for two primary purposes: (1) for flood prediction and alerting in the short-term, and (2) drought prediction and evaluation of EbA effectiveness through continuous data analysis in the long-term.

Future work should scale deployment of the developed system to diverse ecosystems, enhance predictive accuracy, and integrate more environmental variables mentioned in the framework. Moreover, real-world validation of the proposed framework with stakeholder during rainfall seasons is crucial. This approach will help refine the framework and maximize its impact on global climate resilience initiatives.

Author Contributions

Conceptualization, M.K. and J.B.M.; methodology, M.K. and E.H.; software, E.H., N.G. and T.N; validation, K.M.; formal analysis, E.H.; resources, Z.U.; data curation, Z.U.; writing—original draft preparation, M.K. and J.B.M.; writing—review and editing, J.B.M., Z.U., and M.K; visualization, F.M. and O.J.S.; project administration, M.K.; funding acquisition, M.K. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

When requested, the authors will make available all data used in this study.

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Conflicts of Interest

The authors declare no conflict of interest.

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