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INTEGRATION OF WEATHER MONITORING-PREDICTION-WATER CONDITIONS IN CORAL CONSERVATION TOURISM AREAS

INTEGRAÇÃO DO MONITORAMENTO METEOROLÓGICO–PREDIÇÃO–CONDIÇÕES DA ÁGUA EM ÁREAS DE TURISMO DE CONSERVAÇÃO DE CORAIS

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Abstract
The coral monitoring system is designed to monitor coral growth and survival rates, integrated with weather forecasts and real-time information on marine environmental conditions at the Bahoi Likupang coral conservation site in North Minahasa Regency. The goal is to provide tourists and attraction managers with information on favorable weather and marine conditions for coral planting. Predictive analysis was performed using the Decision Tree algorithm, which demonstrated an accuracy of 85%, a precision of 0.83, and a recall of 0.87. These results demonstrate the model's ability to predict rainfall and identify patterns of relationships between environmental parameters. Field trials demonstrated that the IoT system is capable of transmitting real-time data to a web-based dashboard to display sea temperature, humidity, and weather forecasts. The integration of the predictive model and the real-time monitoring system provides an early warning function for potential environmental changes that could threaten coral reef health.

Keywords: Coastal Weather Prediction, Coral Reef Conservation, Decision Tree, IoT Monitoring, Sustainable Blue Economy.

Resumo
O sistema de monitoramento de corais foi desenvolvido para acompanhar o crescimento e a taxa de sobrevivência dos corais, integrando previsões meteorológicas e informações em tempo real sobre as condições ambientais marinhas no local de conservação de corais Bahoi Likupang, no Município de Minahasa do Norte. O objetivo é fornecer aos turistas e aos gestores da atração informações sobre condições climáticas e marítimas favoráveis ao plantio de corais. A análise preditiva foi realizada utilizando o algoritmo Decision Tree, que apresentou 85% de acurácia, 0,83 de precisão e 0,87 de recall. Esses resultados demonstram a capacidade do modelo de prever precipitação e identificar padrões de relacionamento entre parâmetros ambientais. Testes de campo mostraram que o sistema IoT é capaz de transmitir dados em tempo real para um painel baseado na web, exibindo temperatura do mar, umidade e previsões meteorológicas. A integração do modelo preditivo com o sistema de monitoramento em tempo real oferece uma função de alerta precoce para possíveis mudanças ambientais que possam ameaçar a saúde dos recifes de corais.

Palavras-chave: *Economia Azul Sustentável. Monitoramento IoT. Previsão Climática Costeira. Conservação de Recifes de Corais. Decision Tree.*

1 INTRODUCTION

Community-based tourism has been shown to enhance community self-esteem and local participation in rural tourism development (AMIN *et al*., 2023). Marine tourism is a mainstay of Indonesian tourism because it has attractions that can attract tourists to visit Indonesia. One of the tourism developments in Bahoi Likupang is coral conservation tourism, where tourists can directly participate in environmental conservation efforts through coral planting attractions. Furthermore, this conservation tourism provides an economic impact for the local community by providing new jobs. Previous research conducted by TANGIAN *et al*. (2024) found that the environmental conditions of Bahoi Likupang's waters for coral transplantation were 93 (very suitable). The coral survival rate in the first month of transplantation averaged 0.96 cm from 7 coral species taken, with an average survival rate of 98.6%.

Technological advances such as the Internet of Things (IoT) and machine learning are opening new opportunities for improving marine environmental management systems. IoT sensors enable the collection of real-time data on ocean temperature, salinity, turbidity, and atmospheric variables, while algorithms such as Decision Trees can be used to analyze and predict environmental change patterns based on large, dynamic field data sets. Low-cost multiparameter loggers such as EmerSense have been successfully used for marine environmental monitoring (POQUITA-DU; DU; TODD, 2023). Previous research has shown that Decision Trees have high interpretability and greater than 85% accuracy in environmental data classification and water quality prediction (BAI *et al*., 2024; RAHMAN *et al*., 2023).

The integration of real-time monitoring and data-driven predictive models enables the implementation of adaptive environmental management systems that respond to changing ocean conditions. In the context of coral reef conservation areas, this integration can serve as an early warning system to prevent the impacts of thermal stress or coral bleaching due to rising sea surface temperatures above 30°C (LITTLE *et al*., 2022). Sustainable marine resource management, supported by adaptive management strategies and innovative technologies, is foundational to realizing a blue economy that balances ecological integrity with socio-economic benefits (PRIHATMANTO; KETAREN; SUKOCO, 2024).

One effort to support tourism is to create a technological innovation capable of sustaining its sustainability. The resulting technological innovation is a coral growth monitoring tool integrated with a real-time weather and aquatic environmental information system on-site using Android. This system combines IoT sensors and Decision Tree algorithms to generate real-time environmental data visualizations and support evidence-based decision-making. Implementation of this system is expected to increase the effectiveness of coral reef rehabilitation activities, support sustainable marine tourism, and strengthen coastal resilience to climate change.

Therefore, this study aims to develop and implement an integrated coral monitoring system that combines real-time IoT-based environmental measurements with a Decision Tree predictive model to support coral conservation tourism in the Bahoi Likupang region. This research is significant in enhancing the decision-making capacity of tourists, local communities, and site managers by providing timely and accurate information on weather and marine conditions to ensure safe and effective coral planting activities. The novelty of this work lies in the integration of low-cost multiparameter logging, real-time data visualization, and predictive environmental analytics within a single, field-tested system specifically designed for coral reef conservation tourism. Through this approach, the study contributes to advancing adaptive marine environmental management, strengthening community-based tourism practices, and promoting sustainable blue economy initiatives by offering an early warning mechanism capable of anticipating environmental fluctuations that may threaten coral health.

2 LITERATURE REVIEW

The development of IoT technology in the last decade has opened up significant opportunities in marine environmental monitoring systems. IoT is a network of interconnected devices that collect and exchange data, enabling real-time monitoring and data-driven decision-making (GUBBI *et al.*, 2013). Adaptive environmental management involves learning from outcomes of implemented strategies to improve policies and practices over time (WALTERS; HOLLING, 1990). Real-time environmental monitoring using a LoRaWAN-based IoT sensor network has been shown to reliably track water quality parameters in aquaculture settings, demonstrating the feasibility of low-power, long-range marine monitoring systems (BATES; PIERCE; BENTER, 2021). A review by XU *et al*. (2019) also describes how IoT can be used to monitor critical ocean parameters such as temperature, dissolved oxygen, and tides through wireless sensor networks and a cloud platform. Recent monitoring strategies have increasingly shifted from traditional methods toward combining remote sensing imagery with deep learning techniques for improved classification (PIÑEROS; REVELES-ESPINOZA; MONROY, 2024).

On the other hand, the use of machine learning to predict marine weather conditions is also increasingly being applied. According to KIM; KIM; and KIM (2023), models based on decision trees (including ensemble trees) show competitive performance on the task of classifying local weather phenomena such as fog. A review of Machine

Learning implementations on edge/IoT architectures shows that lightweight tree and ensemble models are easier to deploy on capacity-limited devices than full-fledged deep learning models (GAMAZO-REAL; FERNÁNDEZ; ARMAS, 2023). A study by ITZKIN *et al*. (2025) showed that decision tree models can predict coastal wave run-up more accurately than traditional empirical models.

Beyond IoT, a number of other technologies are also beginning to be applied in coral reef monitoring activities. For example, several recent studies have utilized autonomous robotic systems to conduct continuous coral surveys and perform image analysis in underwater environments. Mapping coral reef habitats using UAV imagery combined with Sentinel-2A satellite data, analyzed through Object-Based Image Analysis (OBIA), has been shown to provide high classification accuracy and broad spatial coverage (AHMAD; PUTRA; DARMENDRA, 2024). KUSUMA *et al*. (2023) successfully implemented sensor buoys in coral reef waters to record oceanographic and meteorological parameters, demonstrating that automated monitoring in the real ocean is feasible. Recent work by REZK *et al*. (2024) demonstrated that a voting-ensemble of tree-based classifiers can be embedded in an IoT-enabled monitoring system to reliably classify water as drinkable vs non-drinkable.

The Decision Tree method is a prominent approach due to its ease of understanding and efficient performance. Research conducted by JUNIANI *et al*. (2025) developed a water quality prediction model using the C4.5 algorithm, a variant of the decision tree, and the results showed good performance in classifying water quality.

In the context of coral reef conservation, research by APPRILL *et al*. (2023) and BURNS *et al*. (2024) emphasized the importance of implementing a sensor-based adaptive monitoring system to detect changes in sea temperature that can trigger coral bleaching.

Based on this review, this research focuses on the integration between the IoT monitoring system and the Decision Tree model to support the adaptive management of coral conservation tourism areas adaptively and based on field data.

3 METHODOLOGY

3.1 Location and time of research

The research was conducted in the coral reef conservation tourism area of Bahoi Village, West Likupang District, North Minahasa Regency, North Sulawesi. This location was chosen because it is a conservation-based tourism area where the primary activities are coral transplantation and coral growth monitoring by the local community. The research activities were conducted from May to August 2024, encompassing system design, device testing, field data collection, and analysis of predictive model results.

3.2 Research design

This study uses the Decision Tree method as the primary approach to predicting ocean-weather parameters in coral reef ecosystems. Coral reef conservation involves protecting reef ecosystems, maintaining biodiversity, and ensuring sustainable use for future generations (WILKINSON, 2008). Decision Trees were chosen because they offer the ability to transparently explain relationships between variables through a decision tree structure. Furthermore, this method is relatively easy to interpret, capable of handling non-linear data, and can identify clear prediction rules to support environmental conservation. With this method, prediction results are not only statistical figures but also rules that can be used as a basis for decision-making.

Furthermore, the Decision Tree method has a very high degree of compatibility with the characteristics of IoT data, which is generally generated in real time and tends to change over time. As sensors continuously transmit information, this algorithm can adapt and update its prediction patterns quickly without relying on the large computational resources typically required by deep learning approaches. This makes Decision Trees much more efficient and practical for use on low-power monitoring devices, which form the basis of the system in this study.

Furthermore, the Decision Tree's ability to highlight and determine which variables have the most significant influence also adds value to the process of formulating conservation strategies. For example, the model can help establish temperature ranges, wind speeds, or other environmental parameters considered safe for marine tourism activities or for coral ecosystem rehabilitation programs. In other words, the Decision Tree's role is not limited to its function as a data analysis tool, but has also evolved into a scientifically based decision-making support instrument that can strengthen the adaptive, responsive, and sustainable management of coral reef conservation areas.

The research stages are carried out in stages as follows:

3.2.1 Data collection

Data collection was conducted using water temperature, turbidity, air humidity, rainfall, and wind speed sensors installed at the coral reef site. These parameters were chosen because they have a direct influence on weather prediction. Based on these parameters, the sensors used were included water temperature sensor, a turbidity sensor, a humidity sensor, a rainfall sensor, and a wind speed sensor (anemometer), which were collected periodically at ten-second intervals to obtain a dynamic picture of environmental conditions.

3.2.3 Data delivery

Collected data is sent in real-time through an IoT-based monitoring system. Communication modules using LoRa, WiFi, or GSM are used to connect sensors to a central server or web monitoring. IoT technology is selected for its ability to transmit data efficiently with minimal energy consumption, making it ideal for long-term monitoring in remote or hard-to-reach areas. The collected data is sent to a cloud-based platform for easy access and predictive analysis. Its low-power, continuous transmission capability and adjustable signal stability further strengthen its suitability for remote marine monitoring applications.

3.2.4 Data preprocessing

Before entering the model, the data undergoes preprocessing that includes removing missing or erroneous values, normalizing all variables to a consistent scale, and detecting or cleaning outliers to reduce bias. This step is essential for ensuring complete, uniform, and reliable sensor data, which improves the accuracy of subsequent analyses and prediction models.

3.2.4.1 Remove error/missing values

At this stage, invalid data and missing values must be identified and then removed or replaced with appropriate estimated values. Sensor data is highly susceptible to interference from environmental conditions, such as high waves, battery degradation, or signal interference. If the data is not cleaned, the predictive model may receive incorrect input, resulting in inaccurate weather classifications or predictions. By correcting or removing problematic values, the dataset becomes cleaner and more representative of actual conditions on the ground.

3.2.4.2 Data normalization or standardization

Each sensor produces data in different units, such as temperature in degrees Celsius, cloudiness in NTU, humidity in percentage, and wind speed in m/s. These differences in scale can cause the model to be more influenced by variables with a wider range of values. Therefore, a normalization or standardization process is necessary to equalize the scale of all variables, so that each parameter contributes equally to the modeling process. This step is crucial so that the Decision Tree algorithm and other algorithms can recognize patterns of relationships between variables more objectively and without bias towards a particular variable.

3.2.4.3 Smoothing or filtering for fluctuating data

Data recorded at very fast intervals, for example, every 10 seconds, often exhibits high levels of fluctuation due to the dynamics of seawater movement, wind gusts, or interference (noise) from electronic devices. To reduce these unwanted variations, smoothing or filtering processes, such as using a moving average or a low-pass filter, are performed to stabilize the signal. Smoothed data allows predictive models to more easily identify key patterns without being affected by momentary changes that don't reflect the overall environmental conditions.

3.2.4.4 Detect and remove outliers

An outlier is a value that falls significantly outside the normal data pattern. For example, a wind sensor might suddenly register a speed of 80 m/s when the weather conditions are not extreme, or a sharp increase in turbidity due to a momentary wave disturbance. Such events are typically caused by sensor errors, physical disturbances, or shifts in the device's position. If outliers are not identified and removed, the Decision Tree model can generate erroneous or biased prediction rules, reducing accuracy. Therefore, outlier detection and handling are crucial steps to ensure dataset quality before entering the model training phase. This stage aims to ensure more accurate predictions and truly reflect actual conditions in the field.

3.2.5 Implementation of the decision tree algorithm

The preprocessed data was then analyzed using the Decision Tree algorithm. This algorithm creates a tree structure where each node represents a specific environmental condition, and the leaves provide predictive outputs, based on increases in sea temperature or turbidity levels. This approach is effective because it produces easily interpretable models, making them readily usable by researchers and policymakers.

In this study, the Decision Tree algorithm was chosen because it has several methodological advantages relevant to the system's needs. First, this model offers a very high level of interpretability, making each generated rule easily understood by tourism area managers, field researchers, and conservation stakeholders. An example rule, such as "If humidity exceeds 80% and sea temperature is above 30°C, then the probability of rain increases," demonstrates how the decision tree structure can generate predictive logic that can be directly applied in daily operational guidelines.

Second, Decision Trees have the ability to process non-linear data and variables that lack a simple linear relationship. This is particularly relevant to coastal environments, where changes in one environmental parameter, such as turbidity levels, do not always directly impact other parameters, such as rainfall or wind speed. With its branch-based separation mechanism, this model is able to identify complex patterns without the need for complex mathematical transformations.

Third, this algorithm is relatively computationally lightweight, making it ideal for use in IoT systems, which typically have limited computing power. Decision Trees can be run on both cloud servers and low-spec edge devices without requiring GPUs or large memory. This advantage allows the prediction system to operate in real time and remain responsive even on modest hardware infrastructure. The decision tree reference image, which was used, is presented in **Figure 1**.

Figure 1

Decision Tree Model for Micro-Local Weather Prediction in Coral Conservation Areas

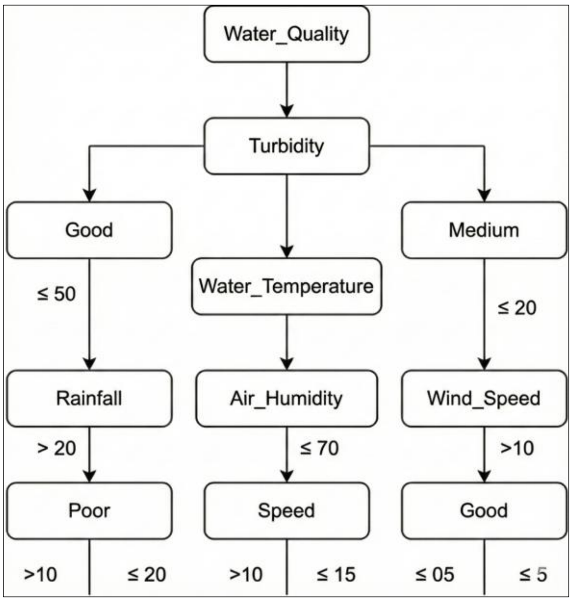


Figure 1 displays the structure of the Decision Tree model used to predict microweather conditions in coral reef conservation areas. The decision-making process begins with the primary parameter, Water Quality, which then branches based on the Turbidity value. If the turbidity is in the "Good" category, the model will consider Water Temperature, then continue with Rainfall and Air Humidity factors to determine whether the final condition is in the "Poor" or "Speed" category. Meanwhile, in the "Medium" branch, the model uses the Wind Speed parameter to assess whether the weather conditions are categorized as "Good." Each decision branch is equipped with a numerical threshold as a separation rule, so the model is able to provide more accurate microweather predictions based on the combination of observed environmental parameters.

Table 1

Environmental Parameters and Their Condition Status

Feature		Good Condition	Currently	Bad
1	Temperature Water	20–30	30–32	<20 or >32
2	Turbidity	0–50	50–100	>100
3	Humidity Air	40–70	70–80	>80
4	Rainfall Rain	0–10	10–20	>20
5	Wind velocity	0–5	5–10	>10

Table 1 presents the key environmental parameters affecting the study area. Each parameter is categorized into three condition levels: good, current, and bad. Water temperature ranges from 20–30°C, as good, while values below 20°C or above 32°C are considered bad. Turbidity is acceptable at 0–50 NTU; increasing turbidity indicates deteriorating water quality. Air humidity, rainfall, and wind velocity are also classified to indicate favorable, moderate, or unfavorable environmental conditions for the ecosystem.

With this methodology, the research is expected to be able to produce a monitoring-prediction system that not only presents real-time data but also provides the ability to project environmental conditions, so that it is more useful in efforts to conserve coral reef ecosystems.

4 RESULTS

This test was conducted on the training model using 1000 training data and 200 test data.

Table 2

Performance Metrics of Rainfall Prediction Model

Metric	Mark
Accuracy	85%
Precision (Rain)	0.83
Recall (Rain)	0.87
F1-Score (Rain)	0.85

The evaluation results in **Table 2** (85% accuracy, 0.83 precision, 0.87 recall, and F1 0.85) indicate that the Decision Tree is capable of capturing patterns in the test data, including humidity, temperature, and rainfall, which are key factors in rain occurrence, as well as wind speed data. This model is suitable as a baseline model for micro-local weather prediction at sea.

Errors in the model can occur under certain environmental conditions. A false positive, indicated by a precision value lower than 1.0, may arise when the humidity is high, and the temperature is suitable, but the wind moves the clouds away from the reef or buoy location, causing the model to predict rainfall that does not actually occur. Conversely, a false negative, reflected by a recall value below 1.0, can happen when local rainfall forms suddenly due to wind patterns or topographic effects that are not captured by the sensor, resulting in missed rain events.

4.1 Field system testing

Field trials of the system, using the prediction web interface, indicate a 65% probability of rain. If rain does occur, it will be categorized as moderate rain accompanied by strong winds and high humidity. This conclusion is based on a series of data transmitted by various sensors at the observation location, which is then processed and analyzed using a Decision Tree model to produce predictive output that can be interpreted by users.

Rainfall is more likely to occur under specific environmental conditions. High air humidity, with relative humidity (RH) of 80% or higher in the lower atmosphere, indicates that the air is saturated with water vapor, as supported by field measurements showing 80.2%. Elevated sea surface temperatures (SST) around coral reefs, typically in the range of 28–30°C, enhance evaporation and increase the supply of water vapor, with field data recording 31.3°C. SSTs between 27°C and 31°C further contribute to evaporation, high humidity, and the potential for convective cloud formation, whereas temperatures below 26°C reduce the energy available for evaporation, decreasing rainfall potential. Very low temperatures, below 25°C, generally inhibit the formation of rain clouds; field observations recorded 29.4°C. Additionally, surface wind speed, measured 10 meters above sea or land, plays a critical role. Wind speeds of 5–15 knots (9–28 km/h) facilitate the transport of water vapor toward land, supporting rain cloud formation. Conversely, winds weaker than 3 knots fail to carry water vapor effectively, while very strong winds exceeding 20 knots (37 km/h) tend to disperse clouds, except during storms or convergence systems. Field data recorded an unusually high wind speed of 34 m/s (122.4 km/h), which may affect local rainfall patterns.

From the field data from testing using monitoring 1/Location 1/buoi 1, it shows that the system as a whole is running well, namely, data from the sensors can be monitored, as can the features for prediction.

Figure 2

Field Trial of Prediction Web View System

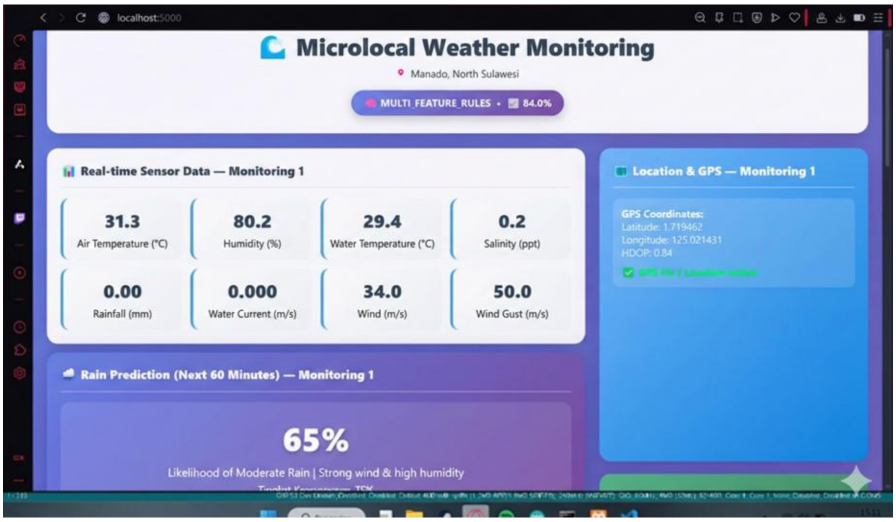


Figure 2 displays the web monitoring system interface, which displays weather predictions based on data generated by temperature, humidity, and wind speed sensors. This display allows users to see the likelihood of rain in real time at the Bahoi Likupang coral conservation site, allowing them to determine the best time for coral transplantation or other tourism activities.

Figure 3

Field Trial of the Location Web View System

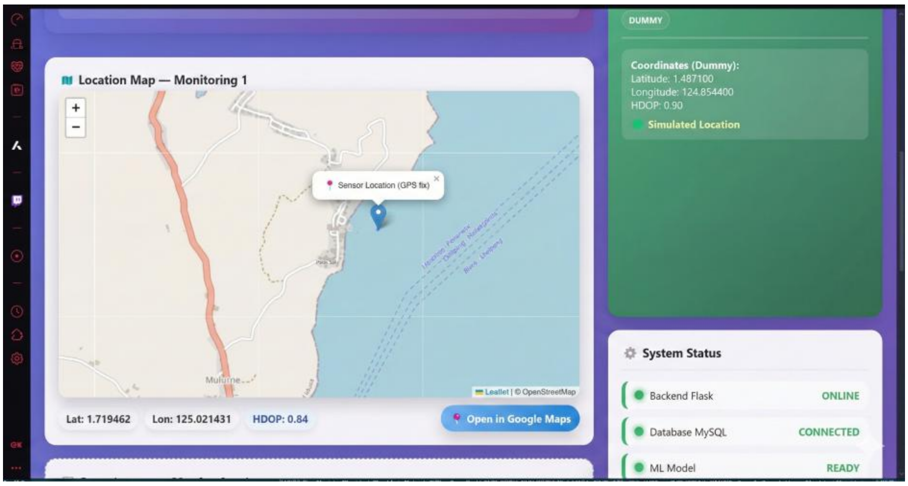
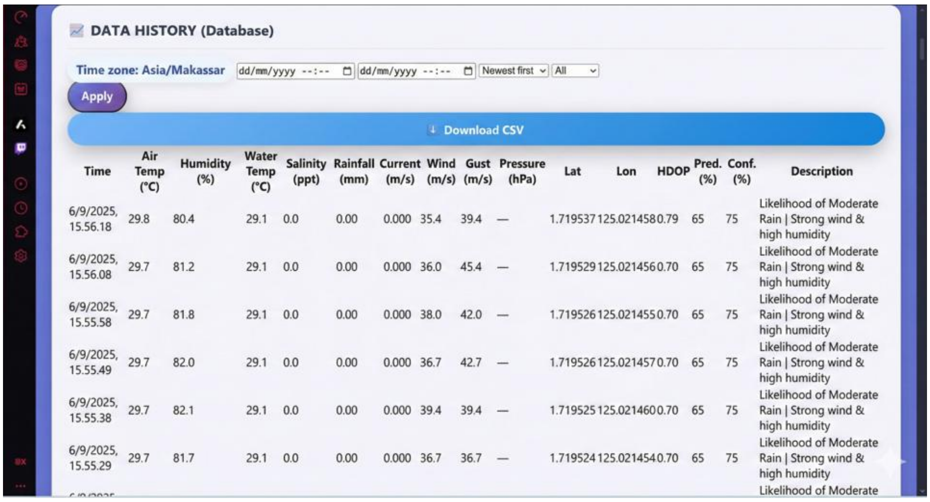


Figure 3 shows an interactive map of IoT sensor locations in Bahoi Village. Each point on the map marks the location of a monitoring site that transmits data on sea temperature, turbidity, and humidity to a central server. This feature helps the village's management monitor the distribution of environmental conditions between locations.

Figure 4

Data Entered in the Field System Trial



Time	Air Temp (°C)	Humidity (%)	Water Temp (°C)	Salinity (ppt)	Rainfall (mm)	Current (m/s)	Wind (m/s)	Gust (m/s)	Pressure (hPa)	Lat	Lon	HDOP	Pred. (%)	Conf. (%)	Description
6/9/2025, 15.56.18	29.8	80.4	29.1	0.0	0.00	0.000	35.4	39.4	—	1.719537	125.021458	0.79	65	75	Likelihood of Moderate Rain | Strong wind & high humidity
6/9/2025, 15.56.08	29.7	81.2	29.1	0.0	0.00	0.000	36.0	45.4	—	1.719529	125.021456	0.70	65	75	Likelihood of Moderate Rain | Strong wind & high humidity
6/9/2025, 15.55.58	29.7	81.8	29.1	0.0	0.00	0.000	38.0	42.0	—	1.719526	125.021455	0.70	65	75	Likelihood of Moderate Rain | Strong wind & high humidity
6/9/2025, 15.55.49	29.7	82.0	29.1	0.0	0.00	0.000	36.7	42.7	—	1.719526	125.021457	0.70	65	75	Likelihood of Moderate Rain | Strong wind & high humidity
6/9/2025, 15.55.38	29.7	82.1	29.1	0.0	0.00	0.000	39.4	39.4	—	1.719525	125.021460	0.70	65	75	Likelihood of Moderate Rain | Strong wind & high humidity
6/9/2025, 15.55.29	29.7	81.7	29.1	0.0	0.00	0.000	36.7	36.7	—	1.719524	125.021454	0.70	65	75	Likelihood of Moderate Rain | Strong wind & high humidity

Figure 4 shows the raw data that the system receives from sensors in the field. This data includes water temperature, air humidity, wind speed, and rainfall over 10-second intervals. This information will then be used as input to a Decision Tree model to generate micro-local weather predictions in coastal areas.

The Decision Tree model used in this study demonstrated adequate performance for analyzing microweather conditions in the Bahoi Likupang coastal area. Based on testing results on 1,000 training data sets and 200 test data sets, an accuracy of 85%, precision of 0.83, and recall of 0.87 were obtained, indicating that the model is able to identify patterns of relationships between temperature, air humidity, wind speed, and rainfall as factors shaping local weather. These results are in line with research by RAHMAN *et al*. (2023), which showed that the Decision Tree model has a high ability to classify environmental data with an accuracy above 85% and advantages in interpretability and transparency of decisions, making it effective for supporting environmental data-based analysis. A similar study by BAI *et al*. (2024) proved that the Decision Tree and Random Forest algorithms are able to achieve 80–95% accuracy in predicting coastal water quality, making them relevant for use in field data-based environmental monitoring systems such as those in this study.

Field research by TANGIAN *et al*. (2024) in Bahoi Village, West Likupang, strengthens the relevance of this research location. Measurement results indicate that Bahoi's oceanographic conditions are highly supportive for rehabilitation and conservation-based marine tourism, with seawater temperatures of 22.6–29.2 °C, salinity of 32.8 ppt, current velocity of 0.17–0.27 m/s, pH 7.04, and clarity reaching 10–15 m. The environmental suitability value reached 93% (categorized as very suitable), indicating high potential for house reef farming activities. However, these rehabilitation activities are still carried out manually using PVC frames and visual observation. This condition demonstrates the need for a digital approach that can provide real-time environmental data to support effective ecosystem management.

Analysis of atmospheric and ocean conditions shows that relative humidity ≥ 80%, sea surface temperature (SST) 29–31 °C, and wind speed 5–15 knots are a combination that increases the potential for rain formation and changes in water clarity. These findings are consistent with research by HU *et al*. (2023), which showed that sea temperatures above 28 °C strengthen convection and evaporation processes in tropical regions. These findings are consistent with LITTLE *et al*. (2022), which showed that rising sea surface temperatures above 30 °C globally cause significant thermal stress on coral reefs and increase coral bleaching events based on NOAA Coral.

4.2 Reef watch satellite monitoring results

Ecologically, monitoring results indicate that relatively stable sea temperatures below 31°C and turbidity levels below 5 FTU still support coral growth and transplantation. These results align with a review by RAZAK *et al*. (2022), which showed that a temperature range of 26–30°C with low turbidity levels is optimal for coral growth and regeneration at restoration sites in Indonesia. The integration of IoT systems with predictive models provides an opportunity to implement the concept of adaptive environmental management, where conservation area managers can adjust tourism activities, coral planting, or research activities based on the latest environmental data. This approach aligns with APPRILL *et al*. (2023), who emphasized the importance of implementing IoT-based sensors and machine learning for adaptive, real-time coral reef monitoring.

Field trials of the system demonstrated that the sensor device was capable of transmitting real-time data to a web monitoring dashboard, displaying sea temperature, humidity, wind speed, and rainfall predictions. This visualization facilitates conservation area managers and tourism operators in determining the best time to carry out coral planting activities and avoid extreme environmental conditions. The resulting early warning system also has the potential to be used in marine disaster mitigation and coral reef habitat protection. Similar findings were also reported by BURNS *et al*. (2024), where a community-based coral monitoring system supported by remote sensing technology was shown to increase adaptive capacity and rapid response to changes in coastal environmental conditions.

5 DISCUSSION

This technology-based approach not only improves monitoring efficiency but also has strategic implications for climate change adaptation policies and sustainable coastal resource management. The results of this study indicate that the integration of IoT devices with Decision Tree predictive models can strengthen the resilience of coastal ecosystems to rapid environmental change. In conservation areas like Bahoi, which are highly dependent on the health of coral reefs as a tourism asset and biological resource, the availability of micro-local weather information is crucial. Real-time monitoring systems provide the ability to detect changes in environmental parameters such as extreme temperature increases, increased waves, or rainfall that can disrupt coral transplantation activities and endanger tourists. Thus, this system provides direct benefits for conservation and community-based tourism management.

These findings confirm that modern technology can overcome the limitations of conventional methods that rely on manual observation, such as assessing water clarity or weather conditions subjectively. Traditional methods are poorly documented and do not represent long-term dynamics. In contrast, sensor systems provide objective, regularly recorded data, enabling comprehensive analysis to support evidence-based policymaking. This approach reinforces the principle of evidence-based decision-making in conservation area management.

Furthermore, further studies of sensor data show that tropical waters are highly dynamic and influenced by various factors, such as convection processes, variations in sea surface temperature, tidal currents, and local wind eddies. This rapid dynamics makes micro-scale weather prediction a challenge. However, the Decision Tree model has proven capable of recognizing important patterns from combinations of environmental variables such as sea temperature, air humidity, wind speed, and turbidity levels. Its easy-to-interpret nature makes this model suitable for non-technical users, including communities in tourist villages.

The integration of the prediction system with the monitoring dashboard also strengthens the concept of an early warning system at the community level. This system allows area managers to identify environmental changes before they impact tourism or coral transplantation. For example, detection of strong winds can provide early warning to temporarily halt marine activities, while spikes in turbidity can indicate sedimentation from land or changes in wave action that could potentially damage young coral. This kind of early warning function is crucial for maintaining ecosystem sustainability.

Analysis of daily trends shows that sea surface temperatures experience a fairly consistent increase from approximately 10:00 AM to 3:00 PM. This temperature increase is then followed by an increase in relative humidity, which can reach over 80%. When temperatures are in the range of 30–31°C, the rate of water evaporation increases significantly, encouraging the formation of convective clouds. This finding aligns with studies of tropical oceanography and is reflected in the structure of the Decision Tree model, where temperature and humidity emerge as key variables in generating rainfall predictions.

In addition to daily patterns, weekly patterns can also be clearly observed, particularly in the turbidity variable. After moderate rainfall, turbidity values show a significant spike due to runoff from the land into the water. This information is crucial for planning coral reef transplantation activities, as high turbidity levels can reduce the light intensity required by zooxanthellae for photosynthesis. Through real-time monitoring, area managers can decide to postpone activities if water conditions have not stabilized.

Another variable that significantly impacts the prediction results is wind speed. During several observation periods, wind speeds reached 30–34 m/s. Under these conditions, although other parameters indicated a tendency toward rain formation, the model predicted the opposite. This indicates that high-speed winds are capable of dissipating moist air masses before condensation occurs, consistent with mainstream theories in coastal meteorology.

Furthermore, this study also revealed that ocean temperature dynamics do not always follow a stable or linear pattern. During several observation periods, temperature fluctuations of up to ±1°C occurred within a relatively short period of time, influenced by variations in local currents and the movement of water masses around the monitoring location. The sensor system used was able to detect these rapid changes in real time, demonstrating the significant advantage of IoT technology over manual measurement methods, which are much less frequent. This phenomenon of short-term temperature changes has important implications for understanding the thermal stress that coral reefs may experience, particularly in transplanted colonies, which are generally more vulnerable.

The integration of sensor data with the Decision Tree model produces a predictive platform that is not only responsive but also capable of predicting environmental conditions with a high degree of accuracy. For example, when the temperature reaches 31.3°C, humidity increases to 82%, and wind speed decreases to around 4 m/s, the model projects a 65% probability of moderate rainfall. This prediction is proven to be consistent with actual conditions in the field, demonstrating the system's effectiveness as an early warning tool for local communities and tourism managers.

Overall, the real-time monitoring system significantly contributes to the implementation of adaptive environmental management. This approach allows decisions related to conservation, rehabilitation, and tourism activities to be made based on constantly updated, real-time data. The visual dashboard interface also facilitates quick community understanding of environmental conditions and enhances the professionalism of Bahoi tourism management, a tourism village focused on ecosystem conservation.

On a broader scale, the use of IoT and artificial intelligence technologies, as developed in this research, has significant potential for implementation in other coastal areas in Indonesia. Many regions face similar challenges, including rapidly changing environmental conditions, limited long-term data, and limited ability to make accurate micro-local predictions. By adopting data-driven systems, coastal communities can increase their adaptive capacity and strengthen ecosystem resilience in the face of climate change impacts.

Thus, integrating real-time sensor data with machine learning models not only yields more precise microweather predictions but also provides the foundation for more adaptive, efficient, and sustainable conservation strategies. This technological approach supports environmental protection while providing added social and economic value to coastal communities.

6 CONCLUSION

This research produces an integrated system capable of monitoring aquatic environmental conditions and predicting micro-local weather in coral reef conservation areas by utilizing IoT sensors and Decision Tree algorithms. This system can transmit real-time data on sea temperature, air humidity, rainfall, and wind speed to a web dashboard, making it easier for managers to monitor environmental changes directly. The Decision Tree model used showed quite good performance, with an accuracy of 85%, a precision of 0.83, and a recall of 0.87, indicating that the model is able to recognize weather patterns influenced by oceanographic and atmospheric variables.

Field testing results demonstrate that the system can provide early warnings of potential rainfall and extreme conditions that could impact tourism and coral transplantation activities. This integration of sensor data and predictive models enables more adaptive, evidence-based environmental management while improving the timeliness of decision-making in the field. This technological approach also demonstrates that IoT-based monitoring is significantly more effective than manual methods because it can quickly detect environmental changes.

Overall, the developed system not only scientifically supports coral reef conservation efforts but also contributes to strengthening community preparedness in facing coastal environmental dynamics. This technology has the potential to be implemented in other coastal areas in Indonesia as part of a marine ecosystem management strategy that is more efficient, sustainable, and responsive to climate change.

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CONFLICT OF INTEREST

The authors state that this research was conducted independently and was not influenced by conflicts of interest, either financially or non-financially, during the implementation, analysis, or reporting of the results. In addition, research is conducted under the principles of academic integrity and applicable research ethics.

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Authors' Contribution

Conceptualization, Diane Tangian and Harson Kapoh; methodology, Harson Kapoh; software, Harson Kapoh; validation, Harson Kapoh and Marson James Budiman; formal analysis, Harson Kapoh and Diane Tangian; investigation, Diane Tangian, Harson Kapoh, Marson James Budiman, Costantein Imanuel Sarapil, Jongky W.A Kamagi, Joneidi Tamarol, Eunike I. Kumaseh, Audy Sumendap, Bernadain D. Polii, Fela Pritian Cera, Alma K. Pongtuluran and Himawan Firga Wibisono; resources, Diane Tangian, Harson

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Data availability

All datasets relevant to this study's findings are fully available within the article.

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