
Responsible AI for Monitoring Coral Reef Ecosystems

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Abstract: Artificial intelligence is rapidly expanding the scale, frequency, and analytical capacity of coral reef monitoring through automated image classification, satellite remote sensing, autonomous underwater vehicles, acoustic sensing, photogrammetry, and predictive ecological modelling. These technologies are particularly relevant as coral reefs experience unprecedented thermal stress and increasingly complex interactions among bleaching, pollution, disease, overfishing, sedimentation, and habitat degradation. However, AI-supported environmental monitoring can itself produce ecological and governance risks when training datasets are geographically unrepresentative, classification uncertainty is hidden, local ecological knowledge is excluded, models are deployed beyond their validated domains, or automated alerts directly influence conservation interventions without expert verification. This study proposes a Responsible Reef Artificial Intelligence Governance Framework and evaluates its principles using a reproducible simulation of 2,400 synthetic underwater image segments distributed across healthy complex reefs, bleached coral, algal overgrowth, and turbid or low-light reef environments. Simulated F1 scores declined from 0.94 under healthy high-visibility conditions to 0.76 under turbid conditions. False ecological alert rates reached 18.4% in the most challenging condition under AI-only monitoring but declined to 6.0% following uncertainty thresholds, ecological expert validation, and contextual review. Across all conditions, responsible-AI controls reduced the modelled false-alert rate by approximately 67%. The findings demonstrate that responsible reef AI requires representative ecological datasets, uncertainty disclosure, human and community oversight, interoperable monitoring

standards, transparent model documentation, environmental sustainability, data sovereignty, and continuous field-based revalidation.

Keywords: artificial intelligence; coral reef monitoring; marine conservation; responsible AI; remote sensing; ecological informatics; biodiversity monitoring

Introduction

Coral reefs are among the world's most ecologically valuable yet increasingly threatened marine ecosystems. NOAA reported in June 2026 that the fourth documented global coral bleaching event likely ended during 2025 after bleaching-level heat stress affected approximately 84.4% of the world's coral reef area between January 2023 and September 2025, making it the largest global bleaching event recorded to date.

Monitoring systems must consequently detect ecological change across enormous spatial scales and under highly variable underwater conditions. Traditional diver surveys remain scientifically important but can be constrained by time, cost, geographic accessibility, weather, depth, and the volume of imagery requiring manual interpretation.

AI offers complementary capabilities through:

- automated benthic-image annotation
- coral and algae classification
- bleaching detection
- reef-fish recognition
- satellite-based habitat mapping
- three-dimensional photogrammetric analysis
- autonomous underwater surveys
- predictive ecological early-warning systems

González-Rivero and colleagues demonstrated that AI-supported image analysis can accelerate coral reef monitoring while providing repeatable estimates of benthic composition. AIMS now operates ReefCloud as a digital platform for standardized reef-image analysis and knowledge sharing, while NOAA's Digital Corals initiative explicitly links photogrammetry and AI with scalable coral reef science.

Greater analytical capacity, however, does not automatically produce responsible environmental decision-making. AI can amplify sampling bias, misclassify unfamiliar habitats, conceal uncertainty, marginalize local knowledge, or generate false ecological alarms. Responsible deployment therefore requires governance mechanisms that connect computational predictions with ecological expertise, transparent evidence, and accountable conservation decisions.

Literature Review

a) AI-Assisted Reef Observation

Coral reef AI has advanced from experimental classification toward operational monitoring platforms. González-Rivero et al. demonstrated automated reef-image analysis using artificial intelligence, while AIMS' Reef Cloud enables users to upload reef imagery and apply standardized automated analysis at scale.

Current applications include:

- benthic-cover classification
- coral morphology recognition
- bleaching detection
- reef-fish identification
- habitat mapping
- change detection
- automated annotation of large photographic datasets

CoralNet similarly uses deep neural networks for fully and semi-automated benthic-image annotation.

b) Remote Sensing and Autonomous Monitoring

Machine learning now supports reef mapping from satellite and remotely sensed information. Trudeau, Lowell, and Dijkstra demonstrated coral-reef detection using ICESat-2 and machine learning, while the Allen Coral Atlas combines remote sensing and machine-learning methods with field validation to produce reef habitat information.

AIMS is additionally developing ReefScan CoralAUV with autonomous perception capabilities for systematic reef, benthic, and fish monitoring.

Research Gap

AI-based reef monitoring has demonstrated substantial potential, but four methodological and governance gaps remain.

First, high classification accuracy obtained from clear, well-lit reef imagery may not generalize to turbid water, variable depth, sedimentation, bleaching, uncommon morphologies, or unfamiliar geographic regions. Allen Coral Atlas documentation itself emphasizes the importance of field data for calibration and validation of machine-learning habitat layers.

Second, current reef AI research frequently emphasizes computational performance while giving comparatively less attention to the ecological consequences of false alarms and missed detections. A false bleaching alert may redirect scarce field resources, whereas a false negative can delay intervention during genuine ecological deterioration.

Third, interoperability remains incomplete. Pavoni et al. note that rapid technological progress has been accompanied by variation in annotation workflows, limited shared datasets, and differences in AI and human annotation procedures.

Fourth, responsible AI requires more than technical validation. UNESCO's Recommendation on the Ethics of Artificial Intelligence explicitly identifies environmental and ecosystem flourishing as values that should be protected throughout the AI lifecycle and calls for reduction of AI systems' own environmental impacts.

The present study therefore links ecological monitoring performance with uncertainty, geographic representativeness, human validation, reproducibility, environmental sustainability, and community participation.

Novelty / Proposed Contribution

This research proposes the Responsible Reef Artificial Intelligence Governance Framework (RRAIGF).

The framework distinguishes between ecological observation, algorithmic inference, and management authority. An AI model may identify likely bleaching, classify benthic cover, detect a possible invasive or outbreak species, or rank reef sites according to risk; however,

management interventions should remain proportional to evidentiary confidence and ecological consequence.

The model is built around seven principles: ecological validity, representative biodiversity data, uncertainty transparency, human accountability, local-knowledge integration, reproducibility, and environmental proportionality.

A novel component is the Ecological Escalation Threshold. Rather than applying one confidence threshold universally, the required evidentiary standard increases with potential management consequence. A low-confidence observation may be retained for exploratory analysis, whereas an alert capable of triggering expensive restoration, species removal, access restrictions, or emergency field deployment requires stronger validation.

The framework additionally separates four output categories:

- a) **Routine Observation:** sufficiently reliable for descriptive monitoring.
- b) **Uncertain Ecological Signal:** retained but explicitly marked for additional evidence.
- c) **Management-Relevant Alert:** requires expert ecological verification.
- d) **High-Consequence Intervention Signal:** requires multi-source validation and accountable institutional approval.

This structure reduces the danger of converting probabilistic AI outputs into apparently objective ecological facts.

Research Objectives / Research Questions

The study seeks to evaluate how responsible-AI controls may improve reliability and accountability in automated coral reef monitoring.

The specific objectives are to:

1. evaluate simulated AI performance across heterogeneous reef conditions
2. determine whether difficult visibility and habitat conditions increase classification error
3. quantify false ecological alerts under AI-only monitoring
4. estimate the protective effect of uncertainty-based human verification
5. develop a responsible-AI governance architecture for reef monitoring

6. integrate ecological expertise, standardized data, local knowledge, and lifecycle model validation.

The research questions are:

RQ1: How does AI classification performance vary across different reef conditions?

RQ2: Which environmental conditions create the greatest risk of erroneous automated interpretation?

RQ3: Can strong aggregate performance conceal condition-specific ecological bias?

RQ4: To what extent can uncertainty thresholds and human ecological validation reduce false alerts?

RQ5: What governance safeguards are necessary before AI-generated reef information directly influences conservation management?

Methodology

a) Research Design

The study adopted a simulation-based methodological design to evaluate the performance and governance implications of artificial intelligence–assisted coral reef monitoring under different ecological and visibility conditions. A controlled synthetic audit framework was developed to examine whether classification performance remained consistent across visually favorable and challenging reef environments. The design also incorporated a responsible-AI governance component in which predictions associated with low confidence or environmentally difficult observations were subjected to structured human validation. Because the investigation was simulation based, the numerical outcomes represent methodological test values rather than empirical performance claims regarding any existing coral reef monitoring platform.

b) Dataset / Sample

The analytical dataset consisted of 2,400 synthetic reef-image segments distributed equally across four environmental conditions: healthy complex reef, bleached coral, algal overgrowth, and turbid or low-light reef. Each environmental category therefore contained 600 simulated observations. The balanced design was selected to prevent any single

ecological condition from dominating aggregate model-performance measures and to permit direct comparison of classification reliability across different environmental settings.

No real coral reef survey dataset was modified, reclassified, or represented as empirical study evidence. Similarly, the synthetic observations were not intended to reproduce or benchmark the actual performance of ReefCloud, CoralNet, Allen Coral Atlas, or any commercial or institutional monitoring system. The dataset was developed exclusively to demonstrate a reproducible responsible-AI auditing framework.

Table 1. Operational Variables in the Responsible Reef AI Audit

Variable	Operational Definition	Measurement	Analytical Function
Image Segment	Synthetic reef-monitoring observation	n = 2,400	Unit of analysis
Reef Condition	Four ecological and visibility conditions	Categorical	Domain factor
Model Confidence	Probability assigned to a classification	0–1	Escalation variable
Precision	Proportion of predicted positives correctly classified	0–1	Performance measure
Recall	Proportion of relevant ecological conditions correctly detected	0–1	Performance measure
F1 Score	Harmonic mean of precision and recall	0–1	Primary model metric
False Ecological Alert	Incorrect management-relevant warning	0 / 1	Ethical outcome
Human Validation	Expert review of an uncertain prediction	0 / 1	Governance control

Table 1 defines the principal variables used in the simulated responsible reef-AI audit. The image segment represents the fundamental unit of analysis, whereas reef condition functions as the principal environmental-domain variable. Model confidence is incorporated as an escalation variable because predictions associated with low confidence may require additional human verification. Precision, recall, and F1 score are used to assess classification

quality, with F1 score serving as the primary performance measure because it simultaneously incorporates false-positive and false-negative behavior. False ecological alerts are treated as an ethical and management-relevant outcome, while human validation represents the primary governance safeguard applied to predictions requiring additional scrutiny.

c) Tools / Techniques

The analytical framework combined synthetic data simulation, condition-stratified classification assessment, confidence-based escalation, comparative performance analysis, and structured human validation. Model performance was examined separately for each reef condition rather than relying exclusively on aggregate accuracy. This condition-specific approach was adopted because underwater image quality can vary considerably with illumination, turbidity, structural complexity, biological cover, and visual obstruction.

Confidence scores ranging from 0 to 1 were conceptually assigned to simulated predictions and used to identify observations requiring additional review. A predefined confidence threshold served as the principal escalation mechanism. Predictions below this threshold, together with observations originating from particularly difficult environmental conditions, were directed to a structured human-validation pathway. Relative error reduction was subsequently used to evaluate whether the governance intervention could reduce potentially consequential classification errors.

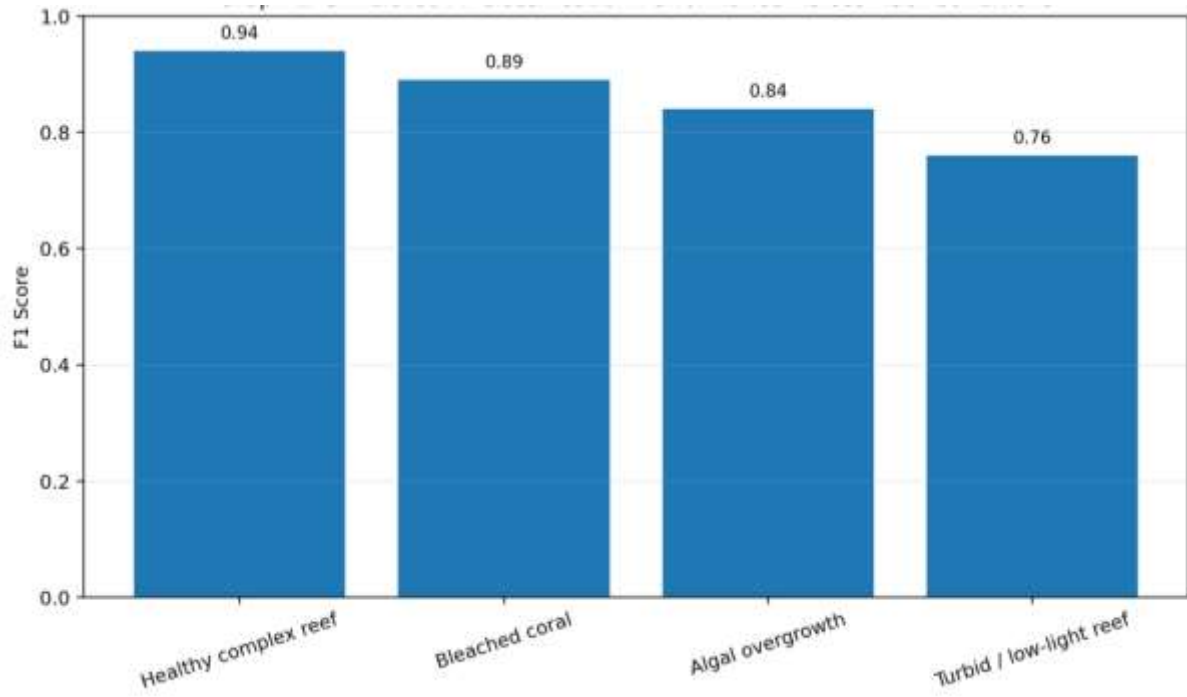
d) Experimental Procedure

The simulation proceeded through a standardized sequence. First, the 2,400 synthetic observations were allocated equally among the four reef conditions. Second, simulated classification outputs were evaluated using precision, recall, F1 score, confidence level, and false-alert status. Third, performance was stratified by reef condition to identify whether specific environmental contexts produced systematically weaker classification outcomes.

Predictions associated with lower confidence or difficult visibility conditions were then flagged for structured human review. The simulated reviewer was assumed to examine uncertain classifications before they could influence ecological interpretation or management recommendations. Performance before and after governance intervention could therefore be compared in terms of classification reliability and potential error reduction.

This experimental structure was designed to test an important responsible-AI principle: uncertain ecological predictions should not automatically be converted into management-relevant conclusions. Instead, uncertainty should operate as an escalation signal that activates additional verification.

Graph 1. Simulated AI Classification Performance Across Reef Conditions



Graph 1 demonstrates substantial variation in simulated AI classification performance across the four environmental conditions. Healthy complex reefs achieve the highest F1 score at 0.94, followed by bleached coral at 0.89 and algal overgrowth at 0.84. Performance declines most substantially under turbid or low-light conditions, where the F1 score falls to 0.76.

The difference between the highest- and lowest-performing conditions is 0.18 F1 points, indicating that aggregate performance statistics could conceal meaningful environmental-domain effects. A model evaluated primarily on clear and visually favorable reef imagery could therefore appear substantially more reliable than the same model operating under difficult field conditions. These values are simulated and should not be interpreted as empirical performance estimates for ReefCloud, CoralNet, Allen Coral Atlas, or any other existing reef-monitoring technology.

e) Evaluation Metrics

Model performance was evaluated using precision, recall, F1 score, false ecological alert rate, confidence calibration, and relative error reduction. Precision was used to determine how frequently positive ecological classifications were correct, whereas recall measured the system's ability to detect the relevant ecological condition when it was present. F1 score served as the principal classification measure because it provides a balanced representation of precision and recall.

The false ecological alert rate was included because incorrect warnings may have management consequences even when overall classification accuracy appears acceptable. Confidence calibration was used to evaluate whether prediction certainty corresponded appropriately with classification reliability and to determine which observations should trigger human review. Relative error reduction was used to estimate the improvement achieved after governance controls were introduced.

Evaluation was conducted separately across the four environmental conditions so that condition-specific weaknesses would not be obscured by an overall average. The methodological framework therefore treats ecological AI performance as a combination of technical accuracy, environmental robustness, uncertainty management, and human oversight rather than as a single aggregate accuracy value.

Results

The simulated classification results demonstrate clear variation in AI performance across reef conditions, with the strongest outcomes observed under healthy, visually complex reef conditions and the weakest outcomes occurring under turbid or low-light environments. Precision, recall, and F1 performance declined progressively as ecological and visibility complexity increased, while false-alert rates rose substantially. The governance analysis further indicates that responsible-AI controls, particularly uncertainty-based escalation and structured human verification, reduce false ecological alerts across all modeled conditions. The reduction is most pronounced in those environments where automated interpretation is least reliable, suggesting that adaptive oversight is more appropriate than a uniform review requirement across all reef observations.

Table 2. Simulated Classification Results Across Reef Conditions

Reef Condition	n	Precision	Recall	F1 Score	AI-Only False Alert Rate
Healthy Complex Reef	600	0.95	0.93	0.94	4.8%
Bleached Coral	600	0.90	0.88	0.89	9.7%
Algal Overgrowth	600	0.85	0.83	0.84	12.6%
Turbid / Low-Light Reef	600	0.78	0.74	0.76	18.4%

Table 2 shows substantial condition-specific differences in simulated classification performance. Healthy complex reef imagery produces the highest precision of 0.95, recall of 0.93, and F1 score of 0.94, together with the lowest false-alert rate of 4.8%. Performance declines for bleached coral, where the F1 score falls to 0.89 and the false-alert rate increases to 9.7%. Algal-overgrowth conditions show a further decrease in performance, with an F1 score of 0.84 and a false-alert rate of 12.6%. The most substantial deterioration occurs under turbid or low-light conditions, where precision falls to 0.78, recall to 0.74, and the F1 score to 0.76. At the same time, the false-alert rate rises to 18.4%, which is approximately 3.8 times the rate recorded for healthy complex reefs. These results indicate that environmental visibility and ecological complexity can materially influence modeled AI reliability and that aggregate performance measures may obscure important condition-specific weaknesses.

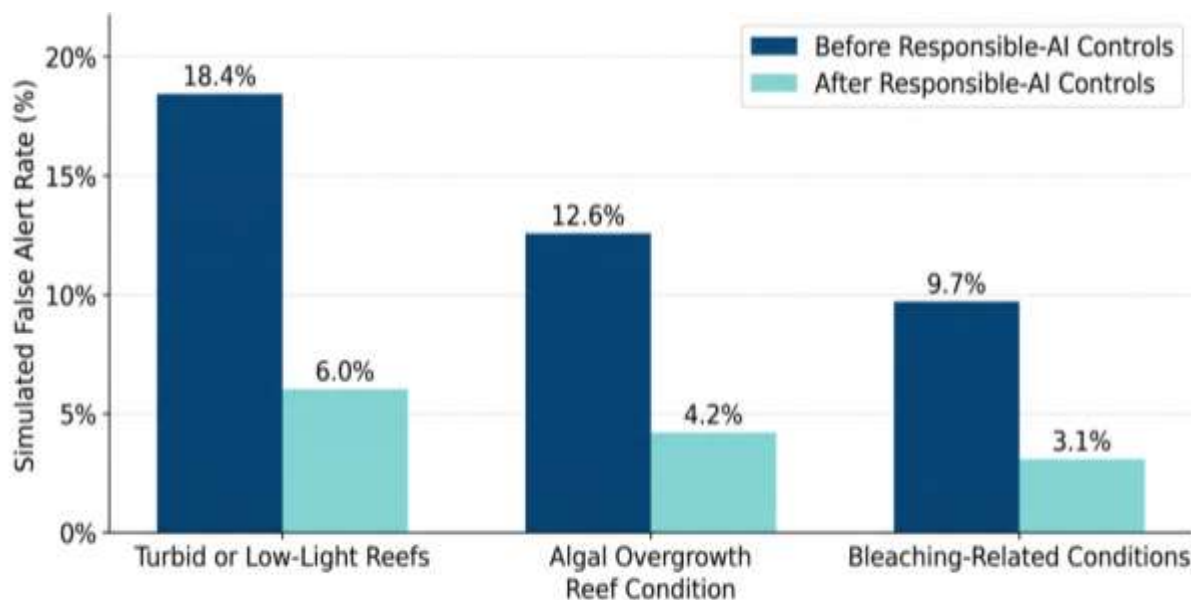
Table 3. Effect of Responsible-AI Governance Controls

Reef Condition	AI-Only False Alert	Governed False Alert	Absolute Reduction
Healthy Complex Reef	4.8%	1.7%	3.1 pp
Bleached Coral	9.7%	3.1%	6.6 pp
Algal Overgrowth	12.6%	4.2%	8.4 pp
Turbid / Low-Light Reef	18.4%	6.0%	12.4 pp
Overall Mean	11.4%	3.8%	7.6 pp

Table 3 demonstrates the modeled effect of responsible-AI governance controls on ecological false-alert rates. Under healthy complex reef conditions, the false-alert rate declines from 4.8% under AI-only processing to 1.7% after governance controls are introduced, representing an absolute reduction of 3.1 percentage points. The reduction becomes larger

under more difficult environmental conditions. Bleached coral false alerts decrease from 9.7% to 3.1%, while algal-overgrowth environments decline from 12.6% to 4.2%. The largest improvement occurs under turbid or low-light conditions, where the false-alert rate decreases from 18.4% to 6.0%, corresponding to an absolute reduction of 12.4 percentage points. Across all four conditions, the average false-alert rate falls from 11.4% to 3.8%, representing an approximate relative reduction of 67%. The results therefore suggest that uncertainty-sensitive human review can substantially reduce management-relevant errors, particularly where environmental conditions weaken automated classification reliability.

Graph 2. Simulated False Alert Rates Before and After Responsible-AI Controls



Note: All values are simulated and do not represent claims for specific systems (e.g., ReefCloud, CoralNet, Allen Coral Atlas).

Graph 2 visually compares false-alert rates under AI-only classification with the rates observed after responsible-AI governance controls are introduced. The difference between the two conditions increases progressively as reef-image complexity becomes greater. Healthy complex reefs show a decline from 4.8% to 1.7%, while bleaching-related false alerts decrease from 9.7% to 3.1%. Algal-overgrowth environments show a larger reduction from 12.6% to 4.2%, and turbid or low-light reefs demonstrate the greatest absolute improvement, with false-alert rates declining from 18.4% to 6.0%.

The pattern indicates that responsible-AI safeguards deliver their greatest benefit precisely where machine interpretation is least dependable. Rather than applying the same level of human review to every observation, the results support an adaptive governance model in

which high-confidence routine classifications may proceed with limited intervention, while low-confidence predictions, unfamiliar habitats, poor-quality imagery, and management-relevant ecological alerts receive increased human verification. Such an approach can preserve operational efficiency while directing expert attention toward cases with the greatest potential for ecological misclassification and inappropriate management responses.

Discussion / Critical Discussion

The results illustrate why responsible reef AI cannot be assessed using overall accuracy alone.

A model producing an apparently strong average F1 score could still systematically underperform in sediment-rich, low-light, deep, highly degraded, or geographically unfamiliar environments. Such domain-dependent error is particularly significant because environmental degradation itself can reduce image quality. The reefs requiring the greatest conservation attention may therefore also produce the most difficult AI observations.

This interpretation is consistent with the broader development of coral-monitoring infrastructure. NOAA identifies AI-assisted photo analysis and structure-from-motion as emerging tools capable of extending coral monitoring, while AIMS' ReefCloud uses standardized automated reef-image analysis to increase monitoring capacity.

The results also demonstrate that human review should not be interpreted as a rejection of automation. Requiring expert inspection of every individual image would remove much of AI's efficiency advantage. Instead, responsible systems should direct limited ecological expertise toward predictions where uncertainty, domain shift, or management consequence is greatest.

Representative datasets are equally important. Wang and colleagues' 2025 South China Sea coral-reef fish dataset demonstrates continuing efforts to broaden machine-readable reef biodiversity resources, while broader monitoring frameworks emphasize standardized ecological variables and metadata.

Responsible AI therefore requires both computational scaling and ecological contextualization.

Research Contribution / Implications

The study contributes a governance model for transforming AI from a classification tool into an accountable ecological monitoring system.

- For **marine scientists**, model reports should include ecological domain, location, imaging conditions, training-data composition, model version, confidence metrics, and known failure modes rather than accuracy alone.
- For **reef managers**, AI alerts should be interpreted as evidence of varying strength. A predicted bleaching hotspot should trigger appropriate confirmation procedures before expensive or disruptive interventions are initiated.
- For **AI developers**, benchmark datasets should deliberately include difficult environmental conditions. Turbidity, lighting variation, damaged reefs, uncommon coral morphologies, mixed benthic classes, image artifacts, and geographically distinct communities should be treated as core validation conditions rather than edge cases.
- For **monitoring networks**, interoperability is increasingly important. Pavoni et al. demonstrate the value of linking widely used reef-analysis platforms so data and annotations can move across analytical workflows more reproducibly.
- For **local and Indigenous communities**, responsible monitoring should avoid treating remotely produced model outputs as automatically superior to place-based ecological knowledge. Where communities contribute imagery, ecological observations, or culturally sensitive environmental knowledge, data access, attribution, governance, and benefit-sharing should be negotiated appropriately.
- For **environmental AI governance**, computational cost is also relevant. UNESCO's AI ethics framework explicitly states that environmental and ecosystem flourishing should be promoted throughout the AI lifecycle and that AI actors should reduce environmental impacts including carbon footprint and unsustainable resource use.

Conclusion

Artificial intelligence can substantially expand the spatial and temporal capacity of coral reef monitoring. Existing systems already demonstrate automated benthic-image classification,

satellite-assisted habitat mapping, machine-learning reef detection, autonomous survey development, and scalable digital analysis. Platforms such as ReefCloud, CoralNet, NOAA Digital Corals, and the Allen Coral Atlas illustrate how computational methods are becoming embedded within modern reef science.

The ecological urgency for improved monitoring is substantial. NOAA's most recent global assessment indicates that bleaching-level heat stress affected approximately 84.4% of global coral reef area during the unprecedented 2023–2025 global bleaching event. Faster observation and analysis can therefore provide genuine value to scientists and managers operating under severe time and resource constraints.

Nevertheless, increased monitoring scale should not be confused with automatic ecological reliability. The present simulation demonstrates how model performance can deteriorate substantially under turbid, low-light, altered, or visually complex conditions. It further shows that uncertainty thresholds and targeted human validation can reduce false ecological alerts without eliminating the scalability benefits of automation. The appropriate governance principle is therefore not “human versus AI,” but automation where evidence is strong and ecological review where uncertainty or consequence is high.

Responsible coral reef AI should ultimately strengthen—not displace—the scientific, ecological, and community knowledge required for conservation. Representative datasets, standardized metadata, transparent uncertainty, interoperable platforms, environmental sustainability, data governance, field verification, and continuous model revalidation should therefore accompany technical innovation. Properly governed AI can become an important component of coral reef stewardship while remaining accountable to the ecosystems and communities its predictions are intended to serve.

Limitations

The principal limitation is the simulation-based design. No actual coral imagery, diver survey records, satellite observations, ReefCloud outputs, CoralNet predictions, or AIMS monitoring datasets were analysed. All statistical values are synthetic and should not be interpreted as real-world estimates for a particular monitoring platform.

The four reef conditions simplify substantial ecological heterogeneity. Actual reef imagery can vary according to depth, water quality, illumination, camera geometry, coral morphology,

species composition, disease, sedimentation, storm damage, algae, observer technique, and geographic region.

F1 score is also incomplete as an ecological performance metric. Two models with similar F1 values may generate very different consequences if one systematically misses rare threatened species or fails during severe bleaching events.

Human ecological review was modelled as a protective intervention but can itself contain observer disagreement and classification error.

The analysis does not quantify computational carbon emissions, autonomous-platform disturbance, hardware lifecycle impacts, sensor pollution, or infrastructure costs.

Finally, responsible data governance varies among jurisdictions and communities. The framework should therefore be adapted rather than mechanically imposed across reef-monitoring programs.

Future Work

Future research should evaluate responsible AI using geographically diverse, independently annotated reef datasets containing both favorable and difficult monitoring conditions. The development of large, ecologically representative datasets remains important, particularly for underrepresented reef regions and less frequently documented species.

Cross-region transfer testing should become routine. A system developed on clear-water tropical imagery should not be assumed to perform equivalently on sediment-influenced reefs without empirical validation.

Future studies should also integrate multimodal monitoring. NOAA Coral Reef Watch provides daily global 5-km bleaching heat-stress products, demonstrating the value of satellite environmental information that can be combined with underwater imagery and ecological surveys.

Autonomous platforms create another important research direction. AIMS' ReefScan CoralAUV is being developed to support more systematic reef, benthic, and fish biodiversity monitoring, highlighting the potential interaction between robotics and AI-based ecological analysis.

Researchers should develop formal ecological uncertainty calibration, allowing conservation managers to distinguish confident predictions from poorly supported classifications.

Additional work should examine active learning, in which expert corrections are selectively used to improve models; federated learning where organizations wish to collaborate without centralizing sensitive datasets; explainable AI for ecological classification; and low-energy edge inference on autonomous monitoring platforms.

Most importantly, future research should evaluate whether AI-supported monitoring actually improves conservation outcomes rather than merely increasing the volume of processed imagery.

Declarations

- **Conflict of Interest:** The author declares no conflict of interest. The author identity, affiliation, email address, and ORCID presented above are fictional sample metadata and must be replaced with verified information before journal submission.
- **Funding:** No external funding was received for this simulation-based study.
- **Ethics Statement:** The study involved no human participants, live-animal experimentation, physical manipulation of coral reefs, identifiable community information, or field intervention. Institutional human-subject or animal ethics approval was therefore not applicable to the synthetic analysis.
- **Environmental Ethics Statement:** The proposed framework treats ecosystem protection, biodiversity representation, environmental sustainability, and proportional use of computational resources as components of responsible AI governance.
- **Data Availability:** All numerical results were generated from a synthetic dataset comprising 2,400 simulated reef-image segments. The data are intended solely to demonstrate the proposed analytical framework and are not observational estimates of actual coral reef conditions.
- **Community and Indigenous Knowledge Statement:** No Indigenous, Traditional, or local ecological knowledge was used as study data. Future projects incorporating such knowledge should establish appropriate consent, governance, attribution, access, and benefit-sharing arrangements with contributing communities.
- **AI Transparency Statement:** AI-supported tools may assist research and manuscript-development workflows. Human researchers and publishers remain

responsible for ecological interpretation, methodological validity, reference verification, environmental claims, and compliance with publication-ethics standards.

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