Oceanography & Fisheries
Open access Journal
ISSN: 2476-0536

Juniper Publishers
key to the Researchers

Opinion
Volume 19 Issue 3 - May 2026
DOI: 10.19080/OFOAJ.2026.19.556015

Oceanogr Fish Open Access J

Intelligent Oceans: Using AI to Safeguard Reef Ecosystems

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Submission: May 16, 2026; **Published:** May 21, 2026

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Abstract

Climate change and rising ocean temperatures are driving unprecedented coral reef decline through widespread coral bleaching. Traditional diver-based survey programs provide high-quality data but are structurally constrained by funding, logistics, and human processing bottlenecks, leaving critical global blind spots. This paper presents an opinion advocating for the integration of artificial intelligence (AI) to address this immense monitoring mismatch. By pairing automation with high-resolution satellite imagery from programs like Sentinel and MODIS, AI can extend the spatial and temporal footprint of reef monitoring beyond human capacity. While critics rightly highlight risks regarding "black-box" models, false positives, and localized taxonomic or geographic training biases, these limitations are best managed through rigorous out-of-distribution detection, targeted data collection, and keeping human ecologists in the decision loop. Specific methodologies, including Random Forest algorithms for structured environmental data and Convolutional Neural Networks for image classification, offer scalable, cost-effective pathways to automate and accelerate stress detection. Ultimately, responsibly deployed AI workflows bridge an essential logistical gap, transforming reef conservation from a reactive posture into a proactive, real-time, global monitoring effort capable of safeguarding vulnerable marine ecosystems.

Keywords: Coral Reefs; Artificial Intelligence; Deep Learning; Coral Bleaching

Introduction

With the increasing threat of climate change and rising temperatures, our oceans, especially our reefs, have been experiencing immense stress. This particularly impacts coral reefs through coral bleaching, a stress response in which corals expel symbiotic algae (zooxanthellae) living in their tissues, leading to reef decline at unprecedented rates [1]. To properly monitor changing reef ecosystems and the spread of coral bleaching, the discipline needs to seriously consider the use of artificial intelligence (AI) in order to track reef health. This paper presents an opinion on why AI should be genuinely considered for tracking reef health, and a brief overview of specific methods, like deep learning, that can be applied.

Deep learning is a branch of AI that uses data and algorithms to build models that can learn and adapt with limited human input. It also uses hidden layers in an artificial neural network to detect deeper patterns and features [2]. AI, and deep learning in particular, has attracted enthusiasm and skepticism in conservation circles. Critics of AI raise concerns such as "black-box" models offering limited interpretability of results, training data can encode geographic and taxonomic biases, and overpromising capabilities risks the misallocation of conservation resources. These objections are grounds for serious engagement and discussion in the broader community. However, the case for AI-based ocean and reef monitoring does not rest on hype itself; it rests on a mismatch between the scale of the monitoring problem and the capacity existing methods have to address it.

The argument for deploying AI in reef monitoring is not primarily a technological one; it is a logistical one. The global reef system spans an estimated 284,300 square kilometers across more than 100 countries and territories [3]. The bleaching events most threatening to these systems are spatially heterogeneous. Individual reef patches within the same region can experience markedly different conditions due to bathymetry and circulation [4,5]. Managing this complexity requires monitoring at fine spatial and temporal resolution, and monitoring that at a global scale is simply beyond the capabilities of any diver-based survey program. Traditional diver-based survey programs such as Reef Check and the Australian Institute of Marine Science Long-Term Monitoring Program have provided invaluable longitudinal data on reef condition, but their spatial reach is fundamentally constrained by diver access, vessel availability, and funding [6-8]. Even the most sustained of these programs monitor only a small fraction of the world's reef area in any given year, and the annotation of collected imagery by trained human analysts introduces additional bottlenecks that limit the extent [9]. The consequence of relying on these approaches has blind spots, including remote atolls, deep fore-reef slopes, and politically inaccessible coastlines, which can go entirely unmonitored. These blind spots may occur in the early and critical stages of bleaching events, when intervention is most likely to succeed. AI does not merely supplement this effort; it addresses an important structural gap that no scaling of conventional approaches can realistically close.

AI-based reef monitoring is not a replacement for in-situ ecological expertise, or a guarantee of accurate detection under all conditions. It is a means of extending the spatial and temporal footprint to monitoring regions and timescales outside human capacity. The relevant question is not whether AI methods are perfect, but whether imperfect AI coverage is preferable to near-perfect coverage of a small, geographically biased sample. Spatial bias inherent in diver surveys is not just a cap in coverage; it distorts the scientific and policy perspective. When global assessments of reef conditions are based disproportionately on well-funded, accessible sites, they systematically underrepresent exactly the reefs most likely to be under-protected. AI systems, if trained with deliberate attention to geographic diversity, can help correct this bias rather than compound it.

Training datasets for AI in ocean applications are disproportionately drawn from well-studied systems, and performance degrades on species assemblages and conditions not represented in training [10]. This is a real limitation; the appropriate response is targeted data collection in understudied regions and the development of bias-mitigation strategies to improve model generalization across diverse marine environments [11]. The concern of bias, as previously mentioned, also affects traditional diver surveys. Diver surveys tend to be geographically biased toward accessible and well-funded sites, systematically under-surveying exactly the remote and biodiverse reefs potentially most in need of protection [12]. AI, if trained responsibly, can extend monitoring to geographies that have been historically absent from conservation literature.

If an AI system generates high false-positive rates for detections, it risks diverting limited response resources away from the genuinely at-risk populations. This concern is especially acute for applications where false negatives carry their own severe consequences [13]. We argue that the appropriate safeguard is not to avoid deployment but to apply rigorous out-of-distribution detection, calibrated uncertainty qualification, and staged deployment protocols. This ensures that human ecologists remain in the decision loop for higher importance interventions. A false positive in an AI bleaching alert costs a field verification dive; a missed event that can cost a reef population. We favor deployment with careful quality controls over non-deployment.

Exploration of AI Methods

Using machine learning or deep learning, types of AI, to monitor coral health could automate the detection of coral bleaching and, in the future, enable prediction before it occurs. Monitoring coral reefs using AI can be seen as a cost-effective and feasible solution, as the analysis phase requires less time, therefore reducing computational time [14]. Due to the models being able to process large amounts of data very quickly, it is possible to analyze coral bleaching on a global scale in real-time, simply due to the use of AI [15].

As mentioned above, traditional reef monitoring relying on divers and underwater photography is accurate but geographically and temporally constrained [16]. Even well-resourced programs can only survey a small fraction of reefs in any given year. Manual analysis of images by humans is not practical for the large volumes being collected by modern survey programs. Satellites, like NASA's Moderate Resolution Imaging Spectrometer (MODIS) or the European Space Agency's Sentinel Program, provide high-resolution and frequently recorded imagery covering most reef-bearing coastlines. These satellites collect visible, near-infrared (NIR), and thermal infrared data, and Sentinel-2 specifically focuses on marine and land monitoring, collecting data on sea surface topography, ocean/land color, and temperature [17]. The data is in abundance; however, the bottleneck is interpretation. Deep learning architectures, each suited to a distinct class of monitoring tasks, offer a scalable path out of this bottleneck.

There is a wide variety of AI methods available that could allow for the automation of tracking reef health in combination with satellite imagery. Random forest (RF) classification, a machine learning algorithm, is a well-established approach for monitoring tasks where structured environmental data is available alongside raw imagery. RF is a machine learning ensemble method that combines multiple decision trees [18]. It enables nonparametric modeling with numerous predictor variables and provides measures of variable importance as part of its output [18]. The algorithm builds many decision trees using bootstrap samples of the training data and, at each split, considers a random subset of predictors.

This approach helps reduce overfitting and enhances the model's ability to generalize to new data [19,20]. RF models have been successfully applied to monitoring seagrass in tropical

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ecosystems, so in theory can be applied to detecting coral bleaching as well [2,21]. The relatively low data requirements and computational overhead make RF models particularly attractive for monitoring programs that operate in data-sparse regions or those with limited infrastructure. This method has been proven to successfully identify and predict coral bleaching on a variety of datasets beyond just temperature readings, leading to faster conservation practices being implemented [22,23].

A mature AI architecture for image-based classification is the convolutional neural network (CNN). Previous studies have demonstrated that CNNs can effectively distinguish between healthy and bleached (stressed) coral reefs. In particular, pre-trained models such as ResNet50 and Inception V3 were evaluated on a dataset of 120 coral reef images [14,24]. These models were tasked with classifying each image as either healthy or stressed, achieving accuracies of up to 90% [14,24].

While CNNs offer significant potential for automated coral bleaching detection, current operational monitoring primarily relies on the NOAA Coral Reef Watch (CRW) framework [25]. This system triggers alerts based on Degree Heating Weeks (DHW) derived from sea-surface temperature (SST) anomalies. Although DHW is a robust predictor of bleaching onset, it is limited to thermal stress metrics and fails to account for the benthic light environment [25]. By leveraging CNNs, researchers can automate detection to facilitate real-time interventions [26]. Utilizing high-resolution imagery from the MODIS sensor and its successor, NASA's Plankton, Aerosol, Cloud, and Ocean Ecosystem (PACE) mission provides a cost-effective pathway for training sophisticated models across vast spatial scales [14,27]. Furthermore, the morphological diversity of coral, which spans various hard and soft taxa and distinct growth forms, often leads to underestimation in traditional imagery analysis [28]. Integrating automated CNN workflows with global datasets is therefore essential to accurately classify diverse coral assemblages and quantify their heterogeneous responses to environmental stress [28,29].

There are many more methods involving AI, such as U-Net semantic segmentation, recurrent neural networks, long short-term memory networks, support vector machines, vision transformers, and generative adversarial networks that can be applied to tracking reef health. Ultimately, these algorithms allow for real-time monitoring and possible prediction of coral reef health due to the automation of these systems in combination with high-resolution satellite imagery. Regardless of the algorithm used, AI reduces the time spent identifying coral health by humans, therefore allowing researchers to be more efficient in their practices [14].

Conclusion

Despite its associated controversy, AI is a very helpful tool for tracking and monitoring coral reef health. As it stands, we do not have the capacity to research and watch coral reefs and bleaching globally without some sort of automation in place. The use of AI algorithms like random forest or CNNs, as described in this opinion, would allow researchers to keep a close eye on the ever-changing ocean ecosystem and respond more quickly in the case of a severe bleaching event. These algorithms also potentially allow for the prediction of coral bleaching, so researchers can use preventative measures rather than reactive solutions. Overall, AI use in this case leads to faster and more efficient monitoring of coral health, ensuring the conservation of these beautiful ecosystems for generations to come.

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