Multi-Source Data Fusion for Harmful Algal Bloom Detection and Prediction: A Survey of Satellite, IoT, and Citizen-Science Approaches Using Machine Learning

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ABSTRACT

Harmful Algal Blooms (HABs) are an escalating threat to freshwater ecosystems, urban water infrastructure, and public health, particularly in densely populated urban water bodies such as Bellandur Lake. Existing monitoring approaches largely rely on a single observation source satellite remote sensing, in-situ sensor networks, laboratory sampling, or citizen-submitted photographs and each of these, taken alone, suffers from well-known gaps: satellite imagery is disrupted by cloud cover, sensor networks are spatially limited, and manual sampling cannot support continuous, real-time monitoring. This paper presents a structured survey of vision- and sensor-driven HAB detection and prediction systems, spanning single-image computer vision techniques, satellite spectral-index-based remote sensing, IoT-based water quality monitoring, and machine learning ensembles such as XGBoost, Support Vector Regression (SVR), and Artificial Neural Networks (ANN). We review recent literature on chlorophyll-a estimation, algal bloom severity classification, and multi-source data fusion, and we examine widely used spectral indices including the Normalized Difference Chlorophyll Index (NDCI) and the Floating Algae Index (FAI). Building on the identified gaps namely the near-universal reliance on a single data modality, the trade-off between detection and prediction capability, and the limited integration of citizen-science data we outline a proposed Multi-Tier Hybrid Monitoring Framework, Eco-Watch, that fuses satellite analysis, IoT sensing, and citizen-submitted imagery within a unified ensemble learning and early-warning pipeline. This survey is intended as a structured reference for researchers and practitioners working toward integrated, real-time decision-support systems for algal bloom monitoring and water quality management.

Index Terms—Harmful Algal Blooms, Remote Sensing, NDCI, Google Earth Engine, IoT Water Quality Monitoring, Citizen Science, Machine Learning, XGBoost, Support Vector Regression, Ensemble Learning, Early Warning Systems

INTRODUCTION

Overview of HAB Monitoring

Water pollution driven by the rapid proliferation of Harmful Algal Blooms (HABs) poses a growing threat to aquatic ecosystems, urban infrastructure, and public health. HABs occur when algae multiply rapidly under favourable conditions such as nutrient enrichment, elevated temperature, and stagnant water, and their excessive growth can deplete dissolved oxygen, disrupt aquatic food webs, and generate toxins harmful to humans and animals. Conventional environmental monitoring approaches generally rely on either physical water sampling or satellite imagery, and each comes with real limitations satellite observations are frequently disrupted by cloud cover, while physical sampling is localized, labour-intensive, andunable to provide continuous coverage. These constraints leave observational gaps that make real-time detection and prediction of blooms especially difficult in complex urban water bodies such as Bellandur Lake.

Over the past decade, advances in remote sensing, the Internet of Things (IoT), and machine learning have opened up new possibilities for automated bloom monitoring. Spectral indices computed from Sentinel-2 and Landsat imagery, low-cost IoT sensor nodes measuring pH, turbidity, and temperature, and citizen-contributed photographs processed with computer vision techniques are all being explored as complementary data sources. However, most published systems remain built around a single modality, addressing detection or prediction in isolation rather than combining these signals into one coherent decision-support pipeline. This paper surveys the current state of this field and proposes a multi-source hybrid framework, Eco-Watch, to help close that gap.

Problem Statement

Despite considerable progress, the fundamental limitation running through most existing HAB monitoring literature is a reliance on a single source of information. Satellite-based systems provide wide-area coverage but are affected by cloud cover and limited temporal resolution; IoT-based systems provide continuous, real-time readings but only at the specific points where sensors are deployed; citizen-science image-based approaches are inexpensive and scalable but depend heavily on image quality, lighting, and the willingness of the public to participate; and machine learning prediction models are frequently trained on a narrow slice of the available environmental data. Furthermore, most studies focus on either detecting the presence of a bloom or predicting future bloom risk, but rarely both within the same pipeline. The absence of an integrated framework that fuses satellite, sensor, and citizen-contributed data remains a significant gap in current research.

Importance for Water Quality Management

Bringing together multiple observation sources into a single decision-support system matters for several practical reasons. Environmental agencies responsible for large or numerous water bodies cannot rely solely on periodic manual sampling, which is expensive and slow to detect fast-developing bloom events. Satellite and IoT data, when combined, allow both broad spatial coverage and point-level, real-time ground truth, while citizen-contributed imagery extends coverage to locations without any fixed infrastructure at all. As urban lakes and reservoirs face intensifying pressure from nutrient runoff and climate-driven warming, an early-warning system capable of flagging bloom risk before it becomes severe can meaningfully support timely mitigation, protect public health, and reduce the ecological damage associated with prolonged, undetected blooms.

Need for Multi-Source Integration

A recurring theme across the literature is that no single data modality is sufficient on its own. Satellite remote sensing offers unmatched spatial coverage but cannot see through clouds and typically has a revisit interval of several days, which can miss short-lived bloom events entirely. IoT sensor networks solve the temporal-resolution problem but are inherently limited to fixed deployment points, making them impractical for monitoring an entire lake or river system. Citizen-science image contributions can fill spatial gaps at near-zero infrastructure cost, but the resulting data varies widely in quality and consistency. Machine learning ensembles that combine tree-based models, kernel-based regressors, and neural networks have shown consistent gains over any single model, suggesting that a similar principle combining heterogeneous sources rather than relying on one should be applied at the data-fusion level as well as the model level.

Contributions of This Survey

The main contributions of this survey are: (1) a structured review of satellite, IoT, and citizen-science based HAB monitoring approaches; (2) an examination of the spectral indices and machine learning techniques most commonly used for chlorophyll-a estimation and bloom severity classification; (3) a comparative analysis of methodologies, data sources, and reported performance across recent studies; (4) identification of the persistent gap around single-modality reliance and the detection-versus-prediction divide; and (5) a proposed Multi-Tier Hybrid Monitoring Framework, Eco-Watch, that integrates satellite NDCI/FAI analysis, IoT-based water quality sensing, citizen-contributed image processing, and an XGBoost–SVR–ANN ensemble within one early-warning dashboard.

Background

A. Harmful Algal Blooms and Environmental Drivers

HABs form when algae, most often cyanobacteria, proliferate rapidly in response to nutrient enrichment (particularly nitrogen and phosphorus runoff), elevated water temperature, and low-flow or stagnant conditions. Urban lakes situated downstream of dense residential and industrial catchments, such as Bellandur Lake, are particularly susceptible because they combine high nutrient loading with limited flushing. Left undetected, blooms can produce cyanotoxins, deplete dissolved oxygen, and cause large-scale fish kills, in addition to generating unpleasant odour and foam that affect surrounding communities.

B. Satellite Remote Sensing and Spectral Indices

Satellite platforms such as Sentinel-2 and Landsat are the most widely used data source for large-area HAB monitoring, primarily because they offer wide spatial coverage without requiring physical access to the water body. The Normalized Difference Chlorophyll Index (NDCI) exploits the reflectance contrast between the red and red-edge/near-infrared bands to estimate chlorophyll-a concentration, while the Floating Algae Index (FAI) is used to detect surface scum associated with severe bloom events. Google Earth Engine (GEE) has become a standard platform for computing these indices at scale, since it provides ready access to processed Sentinel-2 and Landsat archives without requiring users to manage raw satellite data pipelines. The central limitation of this modality is cloud interference, which can leave gaps of several days or more during precisely the periods when rapid environmental change and therefore bloom risk is highest.

C. IoT-Based Water Quality Monitoring

IoT sensor nodes measuring parameters such as pH, turbidity, dissolved oxygen, and temperature provide continuous, real-time, point-level water quality data. These readings act as important ground-truth indicators of the physicochemical conditions that precede bloom formation, and unlike satellite data, they are unaffected by cloud cover. However, sensor deployment is costly to scale across an entire lake or river system, and nodes require regular maintenance and calibration, meaning that IoT data alone can offer depth at a location but not breadth across a water body.

D. Citizen-Science and Computer-Vision-Based Monitoring

Citizen-science platforms that allow members of the public to upload photographs of water bodies have emerged as a low-cost complement to instrumented monitoring. Computer vision techniques colour-space analysis, texture features, and clustering-based segmentation can be applied to these RGB images to estimate bloom presence and severity without requiring any specialised hardware. This approach dramatically increases spatial coverage and public engagement, but the resulting data is inherently variable in quality, lighting, and camera angle, and does not by itself provide the environmental context (nutrient levels, temperature trends) needed for predictive modelling.

E. Machine Learning for Bloom Prediction

Machine learning models most notably Extreme Gradient Boosting (XGBoost), Support Vector Regression (SVR), and Artificial Neural Networks (ANN) are widely used to translate satellite, sensor, and meteorological features into bloom probability and severity estimates. Ensemble strategies that combine tree-based and kernel-based models with neural networks consistently outperform any single algorithm, since each family of models captures different aspects of the underlying, highly non-linear relationship between environmental drivers and bloom formation.

Literature Survey

A comprehensive review of the literature shows steady progress in individual monitoring modalities, alongside a persistent lack of integration between them.

A. Single-Image and Computer-Vision-Based Detection

Park et al. [1] proposed a bloom detection approach that works from a single RGB image, using DBSCAN-based segmentation together with wavelet-based texture analysis to isolate water bodies, followed by three probabilistic algae indices derived from hue and saturation values to estimate bloom intensity. The method achieved close to 94% accuracy in water body extraction and demonstrated effective detection using ordinary smartphone, UAV, and web-sourced images, without requiring expensive multispectral imagery. However, the approach relies solely on RGB information, does not incorporate any environmental parameters, and cannot forecast future bloom occurrence its performance is also sensitive to lighting conditions and image quality.

B. Satellite-Based Ensemble Machine Learning

Kaiser and Qu [2] applied Landsat imagery and Google Earth Engine to large-scale HAB monitoring on the Ohio River, computing NDCI and FAI indices and feeding them into an ensemble of SVR, neural network, and XGBoost models. The system reported a correlation coefficient of 0.85 and an R^2 of

0.82 during validation, successfully identifying bloom events across hundreds of river miles with near real-time processing. The work demonstrates the value of combining spectral indices with ensemble learning at scale, though it remains dependent on satellite revisit frequency and cloud-free conditions, and still requires ground-truth validation to confirm predictions.

Building on a similar theme in a different geographic setting, Joshi et al. [3] evaluated 24 combinations of machine learning algorithms and satellite image sources spanning Sentinel-1, Sentinel-2, and their combination for chlorophyll-a estimation in Phewa Lake, Nepal. An ensemble model combining Support Vector Regression and Random Forest based on Sentinel-2 imagery achieved the best relative performance among the tested combinations, although the authors note that overall predictive accuracy remained only moderate. This finding isnotable for a hybrid framework such as Eco-Watch, as it suggests that even well-designed satellite-ensemble pipelines benefit from additional ground-truth data sources to compensate for the ceiling on accuracy achievable from optical imagery alone in smaller, monsoon-influenced lakes.

C. Systematic Reviews of Remote Sensing and Deep Learning

Wu and Law [4] conducted a systematic review of remote sensing technologies for HAB detection and prediction, with particular attention to recent deep learning advances. Their review examined optical and radar-based detection methods and found that deep learning approaches consistently outperformed traditional spectral-index-based methods across the assessment criteria studied, using Sentinel-2-derived, pixel-level annotated datasets for systematic model comparison. The review also highlights that data labelling and model explainability remain open challenges limiting wider deployment observations that directly motivate the interpretability and ground-truth validation components built into the Eco-Watch framework.

D. Multi-Source Fusion and Explainable AI

Nasios [5] proposed a multi-source fusion methodology that integrates Sentinel-2 optical imagery, Copernicus Digital Elevation Model (DEM) data, and NOAA climate data (temperature, wind) to classify algal bloom severity in small inland water bodies, combining tree-based models and a neural network into an ensemble. The near-infrared and shortwave-infrared Sentinel-2 bands, elevation, temperature, wind, and geographic coordinates were identified as the most informative features for severity classification. This is among the closest analogues to the Eco-Watch approach in the literature, since it explicitly fuses satellite imagery with independent environmental data sources rather than relying on spectral indices alone; its scope, however, does not extend to citizen-contributed imagery or continuous IoT sensor feeds, and it targets severity classification rather than a combined detection-and-early-warning pipeline.

Mermer et al. [6] examined ensemble machine learning together with explainable AI (XAI) techniques for HAB prediction in Lake Erie, comparing ensemble methods Random Forest, Deep Forest, Gradient Boosting, and XGBoost against individual models such as SVM, Decision Tree, and Multi-Layer Perceptron using multi-year

water quality data. The ensemble models were evaluated against these individual baselines for predicting chlorophyll-a concentration as a proxy for bloom severity, with XAI techniques applied to interpret which environmental parameters drove each prediction. This work underscores two points highly relevant to Eco-Watch: ensemble methods offer a consistent accuracy advantage over single models, and explainability is increasingly treated as a first-class requirement rather than an afterthought in environmental prediction systems.

F. Additional Machine Learning and Regression-Based Approaches

Mohan et al. [7] conducted a broad review of how remote sensing and machine learning are jointly used for water quality monitoring and prediction, systematically screening literature across major databases to catalogue the sensors, indicators, and algorithms most commonly paired together. Their review confirms that machine learning models are increasingly favoured over purely physics-based retrieval methods because they better capture the non-linear relationships between spectral reflectance and water quality parameters, but it also notes that most studies remain confined to a single sensor type and a single water body, reinforcing the same single-modality pattern identified elsewhere in this survey.

At the smaller-reservoir scale, Jang et al. [8] built a multiple linear regression model to estimate chlorophyll-a in a narrow estuarine reservoir using two years of Sentinel-2 reflectance data and twenty-one band-ratio and index-based input variables, reporting a coefficient of determination of 0.65. The study demonstrates that Sentinel-2 can resolve spatiotemporal Chl-a patterns even in long, narrow water bodies that are traditionally difficult for satellite-based monitoring, though the comparatively modest R^2 value reflects the same accuracy ceiling that Joshi et al. observed and reinforces the case for supplementing optical retrieval with ground-truth sensor or citizen data.

Working at a much larger scale, Oliveira Santos et al. [9] compared six machine learning algorithms k-nearest neighbours, random forest, extreme gradient boosting, LASSO regression, support vector machines, and the group method of data handling for chlorophyll-a estimation across 149 tropical semi-arid reservoirs in Brazil, using Sentinel-2 bands and spectral indices as predictors. The breadth of this study, spanning an entire multi-reservoir region rather than a single lake, illustrates both the promise and the limits of a purely satellite-driven approach: performance varied considerably across reservoirs with different optical properties, underscoring that no single spectral model generalises well across heterogeneous water bodies without additional local calibration data.

Bu et al. [10] took a fusion-oriented approach closer in spirit to Eco-Watch, combining MODIS-derived optical and thermal variables with heterogeneous meteorological data including sea surface temperature, photosynthetically active radiation, and multiple absorption and scattering coefficients across 192 documented HAB events worldwide. Among seven machine learning models tested, an extreme gradient boosting (XGBoost) regressor gave the strongest predictive performance, reinforcing the tree-based ensemble preference seen throughout this survey. The study is notable for explicitly addressing the false-positive and false-negative problems that arise when HAB detection relies on remote sensing alone, but like Nasios, it stops short of incorporating citizen-contributed imagery or continuous in-situ sensor feeds.

G. Summary and Research Gaps

TABLE 1 Summary Of Reviewed Hab Monitoring Approaches

Study	**Data Source(s)**	**Method**	**ML**	**Key Limitation**
Single-image detection [1]	RGB photos	DBSCAN + probabilistic algae indices	No	No env. context; no prediction
Kaiser & Qu [2]	Landsat, GEE	NDCI/FAI + SVR/NN/XGBoost ensemble	Yes	Cloud cover; needs ground truth
Joshi et al. [3]	Sentinel-1/2	SVR + RF ensemble	Yes	Moderate accuracy; single source

Wu & Law [4]	Optical/SAR	Deep learning vs. index comparison	Yes	Labelling & explainability gaps
Nasios [5]	Sentinel-2, DEM, NOAA	Tree-based + NN ensemble	Yes	No citizen data or IoT feed
Mermer et al. [6]	Water quality records	Ensemble ML + XAI	Yes	No imagery; not real-time
Mohan et al. [7]	Mixed (review)	Systematic literature review	Yes	Single-sensor, single-site studies
Jang et al. [8]	Sentinel-2 (2 yrs)	Multiple linear regression	Yes	Modest R^2 (0.65); single reservoir
Oliveira Santos et al. [9]	Sentinel-2, 149 reservoirs	6-model ML comparison	Yes	Inconsistent cross-reservoir performance
Bu et al. [10]	MODIS + meteorological	7-model ML fusion (XGBoost best)	Yes	No citizen data or IoT feed

Taken together, the reviewed literature reveals four recurring gaps: (1) nearly every system relies on a single primary data modality satellite, sensor, or image rather than fusing them;

(2) studies tend to specialise in either detection or forward-looking prediction rather than a combined pipeline; (3) citizen-science image contributions are rarely combined with quantitative environmental data; and (4) real-time, deployable early-warning dashboards are uncommon outside of large-scale research pilots. These gaps directly motivate the Eco-Watch framework described in the following section.

I. Proposed Methodology: The Eco-Watch Framework

A. System Overview

To address the gaps identified above, this work proposes Eco-Watch, a Multi-Tier Hybrid Monitoring Framework for the detection and prediction of Harmful Algal Blooms. The framework integrates satellite imagery analysis, IoT-based water quality monitoring, citizen-science image processing, and machine learning prediction into a single decision-support platform, structured across five layers: Data Sources, Data Processing, Feature Integration, AI/ML Prediction, and Storage & Visualization.

B. Data Sources and Preprocessing

Multispectral satellite imagery from Sentinel-2 and Landsat is processed through Google Earth Engine to compute the NDCI and FAI indices after cloud removal and image enhancement. In parallel, IoT sensor nodes measuring pH, turbidity, and temperature stream real-time readings, which are filtered and validated to remove noisy measurements. Citizen-contributed RGB photographs, submitted through a web interface, are processed using computer vision techniques to extract colour-and texture-based bloom indicators, providing ground-level validation that satellite and sensor data alone cannot supply. Historical water-quality records and meteorological data are incorporated as additional predictive features.

C. Feature Integration

Satellite-derived spectral features, sensor readings, image-derived indicators, and environmental attributes are combined into a single, unified multi-source dataset. This fusion step is the core distinguishing element of the proposed framework relative to the single-modality systems reviewed in Section III, since it allows the model to draw on wide-area spectral coverage, point-level real-time readings, and crowd-sourced ground truth simultaneously.

D. Machine Learning Ensemble

The integrated feature set is passed to an ensemble consisting of Extreme Gradient Boosting (XGBoost), Support

Vector Regression (SVR), and an Artificial Neural Network (ANN). Each model type captures a different aspect of the relationship between environmental drivers and bloom formation XGBoost handles non-linear tabular feature interactions well, SVR is effective for continuous chlorophyll-a regression, and the ANN can model more complex, higher-order interactions across the fused feature space. The ensemble output yields bloom probability, severity level, and a spatial risk assessment.

E. Dashboard, Visualization, and Early Warning

Prediction results are stored via a MongoDB database and Node.js backend, and surfaced through a React-based web dashboard offering maps, heatmaps, trend charts, and bloom-risk indicators. When predicted risk exceeds a predefined threshold, the framework automatically generates early-warning alerts, closing the loop from raw multi-source data to an actionable notification for environmental authorities and local communities.

II. Comparative Analysis

TABLE 2 Eco-Watch Vs. Reviewed Single-Modality Approaches

Parameter	**Satellite-Only**	**IoT-Only**	**Citizen-Sci.**	**Eco-Watch**
Spatial coverage	Wide	Point-level	Variable	Wide + point + crowd
Continuity	Limited (cloud)	Continuous	Irregular	Continuous
Real-time capability	Limited	Yes	Limited	Yes
Prediction capability	Model-dep.	Rare	No	Yes (ensemble)
Ground-truth validation	Needs ext. data	Inherent	Inherent	Inherent (multi)
Early-warning alerts	Rare	Rare	No	Yes

III. Applications

- **Urban Lake Monitoring:** Supports continuous, multi-source monitoring of urban water bodies such as Bellandur Lake, where single-modality systems currently fall short.
- **Environmental Decision Support:** Provides environmental agencies with a unified dashboard for prioritizing intervention at high-risk sites.
- **Public Health Protection:** Automated early-warning alerts can help prevent public exposure to bloom-affected water during peak severity.
- **Citizen Engagement:** Enables public participation in environmental monitoring through the image-upload interface, extending coverage without additional infrastructure cost.

Challenges

- **Cloud Cover and Temporal Gaps:** Satellite-derived indices remain unavailable during cloudy periods, requiring the sensor and citizen-science layers to compensate.
- **Sensor Deployment Cost:** Scaling IoT sensor coverage across large or numerous water bodies remains expensive and maintenance-intensive.
- **Citizen Data Quality and Consistency:** Crowd-sourced images vary in lighting, angle, and resolution,

complicating automated feature extraction.

- **Data Fusion Complexity:** Combining heterogeneous data types spectral, sensor, image, and meteorological into a single feature space requires careful normalization and validation.
- **Limited Multi-Source Benchmark Datasets:** Few public datasets combine satellite, IoT, and citizen-contributed imagery for the same water body and time period, making direct benchmarking difficult.
- **Model Interpretability:** As highlighted by Wu and Law [4] and by Mermer et al. [6], explainability of ensemble predictions remains an open challenge for building stakeholder trust in automated bloom alerts.

IV. Future Scope

- **Expanded Sensor Networks:** Deploying additional low-cost IoT nodes across more monitoring points to improve spatial granularity.
- **Deep Learning Integration:** Incorporating convolutional and transformer-based architectures for citizen-science image analysis, building on the deep-learning gains reported by Wu and Law [4].
- **Explainable AI Integration:** Adding SHAP- or Grad-CAM-style interpretability layers to the ensemble prediction module, following the direction suggested by Mermer et al. [6].
- **Multi-Lake Deployment:** Extending the framework beyond a single pilot water body to support regional-scale monitoring.
- **Standardized Multi-Source Datasets:** Contributing to the creation of public benchmark datasets that combine satellite, IoT, and citizen-contributed data for the same locations.

CONCLUSION

This survey examined the current state of vision-, sensor-, and satellite-driven approaches to harmful algal bloom detection and prediction, drawing on recent work spanning single-image computer vision, satellite spectral-index ensembles, systematic remote-sensing reviews, and multi-source fusion with explainable AI. The recurring theme across this literature is that no single data modality satellite, IoT, or citizen-contributed imagery is sufficient on its own, and that studies typically specialise in either detection or prediction rather than combining both into a deployable early-warning system. The proposed Eco-Watch framework addresses these gaps by fusing satellite NDCI/FAI analysis, real-time IoT water quality sensing, and citizen-science image processing within an XGBoost–SVR–ANN ensemble, surfaced through a web-based dashboard with automated alerting. While the system is currently under development, the surveyed literature establishes a strong foundation for this integrated approach, and future work will focus on expanding sensor coverage, incorporating deep learning and explainability techniques, and validating the framework across multiple water bodies.

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