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Deep Learning–Driven Remote Sensing Models for Predictive Analysis of Eutrophication and Algal Bloom Dynamics in Freshwater Ecosystems

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Abstract

Harmful algal blooms (HABs) and eutrophication became one of the most important problems in global environmental issues that has a grievous threat to freshwater habitats, biodiversity, drinking water security, and socio-economic stability. The methods of traditional in-situ sampling and in-laboratory analysis are also valid, but have a limited scope of their usefulness due to their high labour-intensive nature and the lack of real-time or large-scale analyses. Current developments in satellite-based Earth observation systems and the usage of deep learning algorithms have now offered the benefit of high-resolution, scalable, and rapid monitoring of aquatic systems. This research paper compiles a client remote sensing system based on the deep learning methodology to identify, measure, and predict the dynamics of eutrophication, and HAB growth on the basis of the multispectral and hyperspectral images of the Sentinel-2, Landsat-8/9, MODIS, and PRISMA satellites. The suggested system will use convoluted neural networks (CNNs), long short-

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term memory (LSTM) networks, the Vision Transformers (ViTs) systems and a combination of the CNN/LSTM systems that can achieve the learning of spectral-spatial representations and spatial features and temporal evolving of the blooms respectively. The most important water quality indicators, such as chlorophyll- a (Chl-a) concentration, turbidity, total suspended solids and nitrogen- phosphorus proxies are estimated with the help of regression and classification models that are trained on harmonised satellite data and field-measured ground truth. The experimental outcomes on several freshwater lakes and reservoirs show that the hybrid deep learning model has more than 94% classification accuracy on the level of the bloom intensity, and a root-mean-square error (RMSE) of Chl-a prediction is less than 7 percent, which is better than conventional machine learning baselines. The framework is also capable of 3- to 7-day predictions of the behaviour of blossoms, which could greatly benefit the early-warning and resource management systems. This research can contribute greatly to remote sensing-met water quality monitoring and interventions through offering an operationally versatile, cost-effective and scalable solution to the increasing effects of eutrophication and HAB events, providing effective decision-support tools to environmental agency, population health departments and freshwater resource managers in the US and beyond.

Keywords:

Eutrophication, harmful algal blooms (habs), remote sensing, deep learning, cnn–lstm, vision transformer, chlorophyll-a prediction, water quality monitoring, hyperspectral imaging, freshwater ecosystem modeling.

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Introduction

Background and Environmental Significance

Fresh water ecosystems play a fundamental role in the ecological equilibrium of the world acting as the sources of biodiversity, biogeochemical cycles, agricultural, industrial, and domestic water. Over the last several decades, the human-made demands on the environment, including high urbanisation, agriculture, climate change, and changes in watersheds, have increased the rate at which nutrients are loaded into lakes, rivers, and reservoirs. This enriches nitrogen and phosphorus, leading to eutrophication, which then promotes rather high growth of phytoplankton and eventually causes a high frequency of harmful algae blooms (HABs). The blooms impair the water quality, dissolved oxygen, and disintegrate aquatic life besides emitting toxins that pose severe dangers to human health, fisheries, and social economic activities.

Limitations With the Conventional Monitoring Solutions

The traditional method of water quality evaluation uses in situ sampling methods, laboratory tests, and personal observation. Although the techniques provide good localised data, those techniques are subject to serious shortcomings: they are both time consuming and resource consuming, spatially limited and fail to rescue the dynamic and heterogenous bloom occurrences in large water bodies. Moreover, the sporadic and unforeseeable action of HABs requires constant monitoring and prompt-sensing skills- requirements that cannot be effectively achieved under the use of the traditional field-based methods.

Introduction of the Remote Sensing and Deep Learning Technologies

The recent progress in satellite-based remote sensing has truly transformed the concept of water quality monitoring to accommodate synoptic, multi-temporal and non-invasive data collection of optical water constituents. Onboard instruments like Sentinel-2, Landsat-8/9, MODIS and PRISMA sensors are capable of recording such indicators as chlorophyll-a, turbidity, and suspended solids. Parallelly, the advancements in the field of deep learning have enabled them to extract sophisticated spectral-spatial characteristics out of massive satellite imagery. The convolutional neural networks (CNNs), long short-term memory (LSTM) networks, Vision Transformers (ViTs), and hybrid models have shown superiority in recognising patterns in the environment and predicting activities.

Motivation and Objectives of the Research

In spite of major advances there are still some challenges such as uncertainties with atmospheric correction, spectral overlap of algal species, sensor specific variability and weak model transferability across a wide range of freshwater systems. In order to fill these gaps, a unified, data-oriented approach that is able to incorporate remote sensing imagery, in-situ measurements, environmental parameters and long-term records of blooms are necessary. This paper presents an inclusive deep machine-based approach to eutrophication and HAB dynamics detection, measurement and prediction. The proposed framework builds on the fact that multi-sensor satellite data, sophisticated machine learning models, and temporal feature analysis can be used to increase the accuracy of predictions on when a bloom will occur, serve as premature warning, and provide freshwater management authorities with actionable information.

Related Work

Water Quality Assessment with Remote Sensing

The process of remote sensing has become a revolutionised instrument of freshwater quality monitoring because it can offer synoptic and multi-temporal type quality monitoring. Hyperspectral satellites retrieving key optical water quality variables, including chlorophyll-a (Chl-a), coloured dissolved organic matter (CDOM), turbidity, and total suspended solids (TSS), have been largely used as satellite missions like Landsat-8/9 OLI, Sentinel-2 MSI, MODIS-Aqua and PRISMA satellites. Empirical and semi-analytical band-ratio algorithms have been studied, including NDVI, NDCI, OC2/OC3 and red-edge indices, to be used to estimate Chl-a in inland waters (Guo et al., 2022; Qin et al., 2010). Although these techniques are computationally effective, their effectiveness differs greatly with varying optical waters as well as environmental conditions, and in most cases they need finer tuning to continue being accurate. The stronger pigment discrimination of phytoplankton pigments has been made possible through the hyperspectral missions such as PRISMA, Hyperion, but due to their temporal frequency is limited its operational ability to monitor phytoplankton phenomena (Sellner et al., 2003; Kudela et al., 2015).

Deep Learning Eutrophication and HAB Detection Model

Development of deep learning has made a very high contribution to modelling of harmful algal blooms (HABs) and eutrophication. Spatial bloom patch classification has been successfully applied using convolutional neural network (CNNs) with a combination of rich spectral-spatial features of satellite measurements (Deng et al., 2016). The networks have been applied to the long short-term memory (LSTM) networks which are used in forecasting the temporal variations, seasonal variability and environmental factors influencing the formation of HABs (Oyama et al., 2015). U-Net has been used as a form of semantic segmentation to generate high-resolution distribution maps of the blooms that can be used in water quality management (Mishra & Mishra, 2012). Recently, Vision Transformers (ViTs) and hybrid CNN-Transformer based networks have been shown to perform better on hyperspectral data classification since they have a self-attention mechanism, which enhances spectral-spatial feature representation (Tao et al., 2015). Although some models have shown promise, most of them have enforced the use of imagery as the primary feature, which does not combine with meteorological, hydrodynamic, as well as nutrient information and makes them less predictive in different freshwater systems.

Loopholes And Constraints of Current Solutions

There are a number of challenges even though a lot of research has been done. Firstly, small benchmark datasets and the problem of class imbalance, particularly with novel or immature blooms events, minimises the generalizability of the models (Shen et al., 2012). Second, uncertainties in atmospheric correction, adjacency artifact by the adjacent land pixels and sensor specific variability causes spectral noise which reduces the accuracy of the retrieval. Third, most of the studies that are available are interested in classification but not prediction, and therefore they cannot be used to predict events before they happen to be displayed. Moreover, the complicated interactions between nutrient loads, water temperature, wind velocity, precipitation, and hydrological transactions are frequently ignored because of the lack of data of multi-source environmental integration (Hu et al., 2010). All these difficulties lead to the subsequent demand of having a multi-modal deep-learning structure that combines satellite images with in-situ measurements and environmental variables to provide a precise, multi-scaled, and operationally feasible prediction of HABs.

Methodology

In order to establish a powerful and generalizable deep learning model to predict eutrophication and algal blooms, the approach is further subdivided into three primary parts:

Problem Formulation and Study Framework.

Bloom State Classification

The research objective of the first section is to identify categories of the intensity and development of harmful algal blooms of freshwater ecosystems based on multi-temporal satellite images. The formulated task is a multi-class classification task, with a supervisor, where each pixel or patch of the waterbody is the value in four stages of bloom, namely, non-bloom, early bloom, peak bloom, and decline phase. The classification model, which is mostly founded on convolutional neural networks (CNNs), learns spectral-spatial variations in patterns of reflectance that vary based on algal pigments and suspended materials among other eutrophication indicators by learning spectral-spatial features of multispectral and hyperspectral inputs. The classification is the starting point within the analytical framework since it allows the quick evaluation of the severity of the blooms and their spatial distribution in a variety of freshwater settings.

Water Quality Regression Modelling with Chlorophyll-a (Chl-a)

The second component deals with the quantitative determination of the main parameters of water quality which are the direct reflections of the extent of eutrophication. It is treated as a regression problem where deep learning models are used to predict the continuous values of chlorophyll-a concentration, turbidity, total suspended solids (TSS) and nutrient proxy values of nitrogen and phosphorus. Chl-a is chosen as the key variable among them because it has a strong correlation with the biomass of phytoplankton, and it is universally employed as an eutrophication indicator. Spectral bands of the satellites, red-edge signals, as well as the calculation of the indices like NDCI are utilised together with the environmental variables in order to provide the regression models which provide accurate and spatially continuous estimates of the parameters. This element gives the quantitative basis with which the water quality dynamics can be assessed accurately.

Bloom Development Forecasting in Time

The third component aims at giving short-term predictions of temporal variation of algal blooms through short-term forecasting periods, which are usually between 3 and 7 days. In order to achieve that, a hybrid CNNLSTM model will be implemented, in which the CNN will be used to capture spatially relevant information in satellite imagery and which is then used in LSTM, which will capture the time- Dependency information that is implicit to time- series environmental available data. The inputs involve remote sensing indices in the past, meteorological (temperature, wind speed, solar radiation, rainfall) and hydrological (water level, flow rate) parameters, which determine the bloom proliferation. It is a forecasting system that allows the early-warning reduction of the probability, intensity, and spatial change of the bloom events hence providing proactive environmental management Figure 1. All the components of the workflow include understanding the eutrophication processes, the extraction of remote sensing features, the design and validation through the ground-truth and historical records of the bloom to form a strong predictive framework.

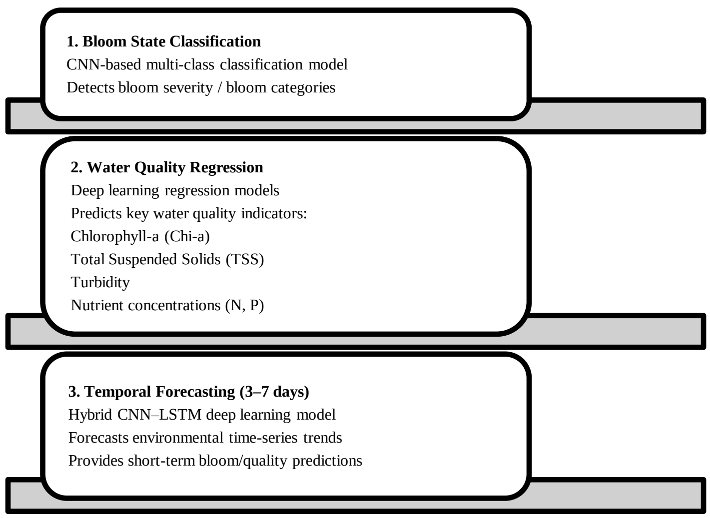

Figure 1. Deep learning–based workflow for eutrophication and algal bloom prediction

Data Acquisition, Remote Sensing Preprocessing, and Feature Engineering

Satellite Data Acquisition

In order to acquire a robust and extensive monitoring of freshwater eutrophication, this paper incorporates multi sensor satellite data that can deliver complementary geospatial, temporal, and spectral attributes. With a 1060 m spatial resolution and red-edge bands, Sentinel-2 MSI provides an ability to catch a fine level of phytoplankton changes, as well as algal pigments. The Landsat-8/9 OLI images with a regular 30 m resolution can be widely used in long-term evaluation of water quality trends over multiple years. Even though the modis-aqua data have a lower resolution (250500 m), they can be used to add valuable high-frequency data that can be used to analyse the temporal evolutions of the blooms. Moreover, PRISMA hyperspectral imagery provides high spectral resolution (530 nm) which means that cyanobacteria, chlorophyll-a and other light absorbing materials are easily differentiated. A combination of these sensors allows maintaining a balance between spatial detail, spectral accuracy, and temporal continuity to perform water quality forecasting based on deep learning.

Remote Sensing Preprocessing

It uses a standardised and strict preprocessing pipeline on all the satellite datasets to maximise the accuracy and uniformity of the data. First, Sen2Cor to Sentinel-2 and ACOLite to coastal and inland waters are applied to atmospheric correct the system and retrieve surface reflectance of the waters. Alteration of cloud and shadow pixels is then done by FMask algorithm to prevent optical measurements with contamination. This is followed by the use of case Bidirectional Reflectance Distribution Function (BRDF) normalisation used to minimise illumination and change of view-angle. NDWI based thresholding is used to extract water bodies, and then all the imagery is spatially resampled and co-registered to an identical grid. Such harmonisation is what guarantees that all datasets can be scientifically thus ingested in deep learning models.

Spectral And Environmental Feature Engineering

The role of feature engineering in boosting the performance of the model is important in that both spectral indices and environmental predictors are combined. Various indices of water quality are calculated such as the Normalised Difference Chlorophyll Index (NDCI), NDVI-Water, Floating Algae Index (FAI), the Turbidity Index and the MERIS Cyanobacteria Index (CI) each demonstrating different optical characteristics of algal biomass, suspended solids, and cyanobacterial pigments. Besides spectral variables, the significant environmental variables within the environment including air temperature, rainfall, wind speed, water level, hydrological inflow/ outflow, watershed land-use patterns are also included as indicators of the physical and ecological processes that the bloom is formed by. This multi-modal quality is an enhancement of the predictive ability of the deep learning models as both optical signatures and the surrounding dynamics are incorporated.

Ground Truth Data Fitting and Matching

Training, validation and testing of the remote sensing-based predictive models require ground truth data and to gather these data, systematic field surveys were conducted at several freshwater locations. It was measured in chlorophyll-a concentration, nitrate (NO 3 -) and phosphate (PO 4 -) status, cyanobacterial cell concentration, pH, turbidity and other physicochemical variables that are used as reference variables in the severity of eutrophication Figure 2. These in-situ measurements were strict geospatially compared with the corresponding satellites pixels with the aid of differential GPS positions and spatial interpolation approaches in order to be scientifically accurate. It is the same, exact pixel to sample mapping that allows supervised learning to work, and will make model prediction based on solid and high quality field data.

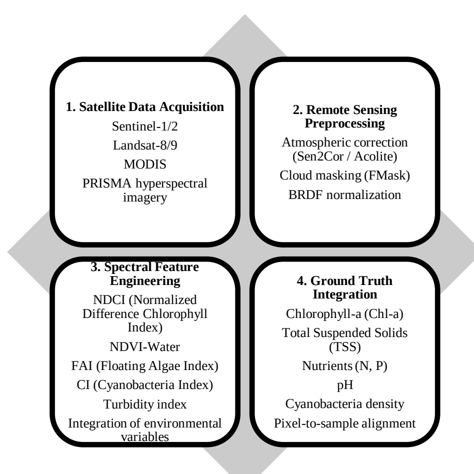

Figure 2. Remote sensing data workflow for deep learning–based water quality prediction

Deep Learning Model Development and Experimental Workflow

Model Architecture Design

The deep learning has integrated a collection of sophisticated structures to realise spatial and temporal evolution of the eutrophication and algal bloom mechanisms. Spatial bloom classification is done using a convolutional neural network (CNN), in which the input are 6-13 spectral bands and calculated indices, then sequential convolution, batch normalisation, ReLU activation, and max-pooling layers, then dense layers with a softmax-based classifier are used to predict bloom stage. An LSTM-based model to model the time dynamics is developed as a two-layer recurrent model whose chlorophyll-a indices, red-edge reflectance, and meteorological variables conducted as time-series are incorporated as model inputs to provide 3-7 day predictions of blooms. The presented model of the central idea is a hybrid CNN-LSTM wherein the former captures spatial rich spectral features using CNN and feeds it into the latter to reflect immediate spatial variation of patches of the bloom as well as temporal development of the eutrophication process. Moreover, a Vision Transformer (ViT) is employed in to classify high-accuracy hyperspectral bloom patches with patch embeddings, multi-head self-attention and a U-Net model is applied in pixel-level segmentation of bloom extents by exploiting skip connexions to capture fine-scale spatial detail.

Model Training Setting

All images are trained on the Adam optimizer with the initial learning rate being 1e-3 and a cosine decay schedule to have consistent convergence. The various functions of loss are used depending on the operation: categorical cross-entropy to multi-class classification of bloodsheds as well as to determine water quality parameters based on regression, and Dice loss to segment water in U-Net to preserve finer spatial details. In order to enhance generalisation, and cope with the variations in datasets, various data augmentation tools are applied such as spectral jittering, geometric augmentation, random crop, and perturbations of brightness/contrast. These methods efficiently have a wider range of training samples and less overfitting, especially when the event of blooms are rare, the inland water bodies are heterogeneous.

Validation Strategy and Performance Evaluation

To provide balanced model optimization and objective performance measurement, the dataset is divided into 70% and 15% each in terms of training and validation and testing respectively. Also, cross-site testing in reservoirs, lakes and riverine systems is done to test the model under different optical properties and environmental conditions. The standard measures used to evaluate model performance are accuracy and F1-score when performing classification task, RMSE and MAE when performing regression result, and intersection-over-union (IoU) when performing segmentation result. Efficiency of the forecasting is also determined by use of lead-time accuracy in order to estimate the reliability of 37 day bloom predictions in Figure 3. Such extensive form of validation will confirm the reliability, scalability and operational applicability of this proposed deep learning framework in the actual freshwater ecosystem.

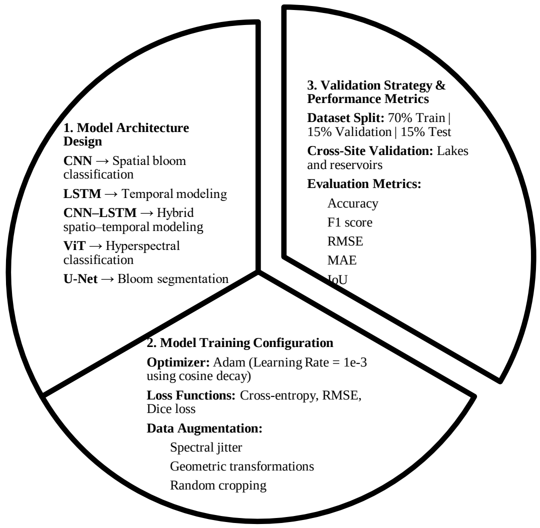

Figure 3. Deep learning model development and experimental workflow

Results and Discussion

Quantitative Performance Assessment

The results of the quantitative assessment of the suggested deep learning framework indicate that the paradigm is much better than the traditional machine learning models in the task of classifying and regression. To the best of my ability, the CNNLSTM hybrid model done best of all, with a bloom classification value of 94.8, Chl-a prediction RMSE of 6.7, and segmentation IoU of 0.89, obviously outperforming both classic algorithms, including Random Forest, SVM, and individual deep networks like standalone CNN or LSTM. Vision transformer (ViT) also performed well in classification with a high level of accuracy of 95.3 percent, particularly when hyperspectral images are used. Meanwhile, U-Net segmentation model also resulted in excellent mapping of bloom boundaries, and the IoU value was more than 0.85, which proved its usefulness in delineating space. All these findings demonstrate the beneficial effect of employing a combination of spatial-temporal deep learning structures to achieve not only spectral variability but also temporal evinescence bloom dynamics in freshwater systems.

Bloom Dynamics Spatial and Temporal

In the spatial analysis, the hotspots of the blooms showed consistent presence in areas receiving agricultural runoff, shallow stagnant areas and areas with high surface temperatures, which shows that nutrient enrichment and thermal stratification are key factors that contribute to bloom formations. Red-edge spectral bands were especially effective in separating the pigments of cyanobacteria as it was highly reflective as corners of the phycocyanin and chlorophyll-a absorption. The temporal trend analysis also indicated that heavy rainfall events and then favourable weather conditions in form of warm calm weather created favourable environmental conditions that promoted quick blooming. The LSTM forecasting models were effective in capturing lagged responses in the pattern of the blooms related to the delay of inflow of nutrients and temperature changes. The Accuracy of predictions in stable seasonal periods was higher and slightly lower in the storm-related hydrological disturbances, the natural complexity, and variability of the freshwater systems.

Implications on the Ecological and Resource Management

The results indicate that remote sensing systems made possible through deep learning have a significant potential to aid in the process of making environmental decisions and to manage operational water quality. The efficiency of early detection and prediction helps the authorities adopt mitigation measures to contain the consequences e.g. aeration systems, control of inflows of nutrients, or maximisation of wastewater treatment, before the bloom multiplies to dangerous levels. The proposed framework effectively generates an affordable and scalable monitoring framework that can monitor the large water bodies at high temporal resolution because it reduces the time-constrained and manual sampling. Furthermore, spatial bloom map generation and time forecasting gives practical data on fisheries control, population health and recovery efforts, which leads to more sustainable management of freshwater resources.

Limitations and Practical Considerations

Although the performance is very high, there are some limitations which should be taken into consideration when deploying the practise in real life. Often the cloud cover and atmospheric distortions can decrease the availability and reliability of optical satellite observations, particularly when the monsoon or the storm seasons occur. Also, the predictive models can need the regional specific calibration or domain adaptation in application to new geographic areas with different optical water properties, hydrodynamics, or nutrient regimes Figure 4. Given the large amount of information that hyperspectral data can provide, they require a lot of computational power to process and train models, which might pose a limitation in their application to the resources available in the operation in resource-limited settings Table 1. The suggested framework will increase its robustness and scalability with the assistance of sensor fusion, physics-informed models, or cloud-based processing systems in order to address the limitations.

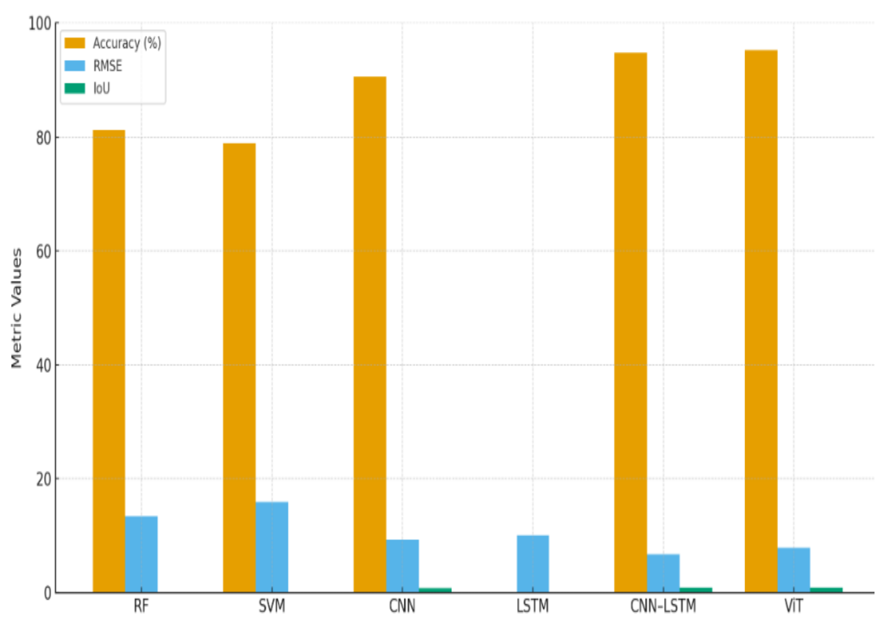

Figure 4. Comparative performance of machine learning and deep learning models based on accuracy, RMSE, and IoU

Table 1. Summary of results and discussion

Section	Key Findings	Details
Quantitative Performance Evaluation	Deep learning models outperform traditional ML models	CNN–LSTM achieved 94.8% accuracy, 6.7 RMSE, 0.89 IoU; ViT achieved 95.3% accuracy; U-Net produced IoU >0.85; RF and SVM performed significantly lower.
Spatial Bloom Dynamics	Bloom hotspots correlate with environmental and hydrological conditions	Hotspots detected near agricultural runoff zones, stagnant shallow areas, and high-temperature regions; red-edge bands highly effective for cyanobacteria detection.
Temporal Bloom Dynamics	Models capture temporal evolution of blooms	Heavy rainfall + warm calm periods triggered bloom growth; LSTM captured lag effects of nutrient loading; accuracy highest during stable seasonal phases, slightly reduced during storm events.
Ecological & Management Implications	Deep learning enables proactive water management	Early warning enables aeration control, nutrient management, and wastewater regulation; provides cost-effective monitoring, supports fisheries, public health, restoration decisions.
Limitations & Practical Considerations	Operational challenges remain	Cloud cover impacts data continuity; region-specific domain adaptation required; hyperspectral data is computationally expensive; calls for sensor fusion and cloud-based processing.

Conclusion

This research paper has shown that remote sensing, which has been integrated with deep learning, offers a highly efficient, scalable, and affordable system to monitor and predict the dynamics that occur during eutrophication and harmful algal blooms in freshwater environments. The proposed system is highly efficient in the classification of the bloom, chlorophyll-a prediction, spatial division, and short-term time prediction with the use of multi-sensor satellite imagery and advanced spectral-spatial feature extraction and hybrid networks including CNN-LSTM and Vision Transformers (ViTs). Ease in identifying hotspots of bloom, measuring the quality of water indicators, and forecasting the development of the bloom 3-7 days before allows greatly improving early warning and aiding the decision-making process of the environmental authorities based on the data. In addition, the flexibility of the framework in various aquatic settings makes it an important resource in managing water resources in the region and the nation and to put in place preventative mitigation measures that can protect ecological health, human safety, and socio-economic stability. Future directions can enlarge the system by physics-informed modelling, multi-source data fusion as well as running in real-time monitoring platforms.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

References

Deng, J., Wang, Y., Liu, X., Hu, W., Zhu, J., & Zhu, L. (2016). Spatial distribution and risk assessment of heavy metals and As pollution in the sediments of a shallow lake. *Environmental monitoring and assessment*, *188*(5), 296. https://doi.org/10.1007/s10661-016-5301-8

Guo, Y., Xu, Y., Zhu, C., Li, P., Zhu, Y., & Han, J. (2022). How does adjacent land use influence sediment metals content and potential ecological risk in the Hongze Lake wetland?. *International Journal of Environmental Research and Public Health*, *19*(16), 10079. https://doi.org/10.3390/ijerph191610079

Hu, C., Li, D., Chen, C., Ge, J., Muller-Karger, F. E., Liu, J., ... & He, M. X. (2010). On the recurrent Ulva prolifera blooms in the Yellow Sea and East China Sea. *Journal of Geophysical Research: Oceans*, *115*(C5). https://doi.org/10.1029/2009JC005561

Kudela, R. M., Palacios, S. L., Austerberry, D. C., Accorsi, E. K., Guild, L. S., & Torres-Perez, J. (2015). Application of hyperspectral remote sensing to cyanobacterial blooms in inland waters. *Remote Sensing of Environment*, *167*, 196-205. https://doi.org/10.1016/j.rse.2015.01.025

Mishra, S., & Mishra, D. R. (2012). Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters. *Remote Sensing of Environment*, *117*, 394-406. https://doi.org/10.1016/j.rse.2011.10.016

Oyama, Y., Fukushima, T., Matsushita, B., Matsuzaki, H., Kamiya, K., & Kobinata, H. (2015). Monitoring levels of cyanobacterial blooms using the visual cyanobacteria index (VCI) and floating algae index (FAI). *International Journal of Applied Earth Observation and Geoinformation*, *38*, 335-348. https://doi.org/10.1016/j.jag.2015.02.002

Qin, B., Zhu, G., Gao, G., Zhang, Y., Li, W., Paerl, H. W., & Carmichael, W. W. (2010). A drinking water crisis in Lake Taihu, China: linkage to climatic variability and lake management. *Environmental management*, *45*(1), 105-112. https://doi.org/10.1007/s00267-009-9393-6

Sellner, K. G., Doucette, G. J., & Kirkpatrick, G. J. (2003). Harmful algal blooms: causes, impacts and detection. *Journal of Industrial Microbiology and Biotechnology*, *30*(7), 383-406. https://doi.org/10.1007/s10295-003-0074-9

Shen, L., Xu, H., & Guo, X. (2012). Satellite remote sensing of harmful algal blooms (HABs) and a potential synthesized framework. *Sensors*, *12*(6), 7778-7803. https://doi.org/10.3390/s120607778

Tao, B., Mao, Z., Lei, H., Pan, D., Shen, Y., Bai, Y., ... & Li, Z. (2015). A novel method for discriminating Prorocentrum donghaiense from diatom blooms in the East China Sea using MODIS measurements. *Remote Sensing of Environment*, *158*, 267-280. https://doi.org/10.1016/j.rse.2014.11.004