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Monitoring, simulation and early warning of cyanobacterial harmful algal blooms: An upgraded framework for eutrophic lakes

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ABSTRACT

Cyanobacterial Harmful Algal Bloom (CyanoHAB) is a global aquatic environmental issue, posing considerable eco-environmental challenges in freshwater lakes. Comprehensive monitoring and accurate prediction of CyanoHABs are essential for their scientific management. Nevertheless, traditional satellite-based monitoring and process-oriented prediction methods of CyanoHABs failed to satisfy this demand due to the limited spatiotemporal resolutions of both monitoring data and prediction results. To address this issue, this paper proposes an upgraded framework for comprehensive monitoring and accurate prediction of CyanoHABs. A collaborative CyanoHAB monitoring network was firstly constructed by integrating space, aerial, and ground-based monitoring means. As a result, CyanoHAB conditions were assessed frequently covering the entire lake, its key areas, and core positions. Furthermore, by overcoming technical limitations associated with high-precision simulation of the growth-drift-accumulation process of CyanoHABs, such as the unclear drifting process of CyanoHABs and the mechanism of its coastal accumulation, the multi-scale CyanoHAB prediction was realized interconnecting the entire lake and its nearshore areas. The implemented framework has been applied in Lake Chaohu for over three years. It provided high-frequency and high-spatial-resolution CyanoHAB monitoring, as well as its multiscale and accurate simulation. The application of this framework in Lake Chaohu had significantly improved the accuracies of CyanoHAB monitoring, simulation, and early warning. This advancement holds significant scientific value and offers potential for CyanoHAB prevention and control in eutrophic lakes.

1. Introduction

The frequent occurrence of cyanobacterial harmful algal blooms (CyanoHABs) in freshwater lakes is a crucial environment problem, causing serious ecological and health damage to both human and aquatic life (Paerl and Paul, 2012; Huisman et al., 2018; Fang et al., 2022). For instance, a significant CyanoHAB event in Lake Taihu during May–June 2007 leaded to a water crisis in Wuxi City (Duan et al., 2009). In September 2013, a serious CyanoHAB occurred in west Lake Erie, resulting in the loss of clean drinking water for nearly 2000 residents in Carol Town, Ohio (Wynne and Stumpf, 2015; Steffen et al., 2017). Furthermore, cyanobacterial toxins had resulted in the sudden deaths of at least 330 African savanna elephants in 2020 (Wang et al., 2021). In fact, CyanoHABs in eutrophic lakes have become prevalent and will exist for a long time in the future (Duan et al., 2020; Wang et al., 2023a; Ma et al., 2023). Hence, efficient monitoring and accurate prediction of CyanoHABs are crucial in affected lakes to mitigate disasters and minimize socio-economic losses.

Timely and accurate assessment of CyanoHABs in eutrophic lakes, yet, remains a significant challenge (Zhang and Zhang, 2015; Tan et al., 2023). Optical satellite remote sensing can achieve large-scale and long-term observation (Kutser, 2009; Shi et al., 2019), which has been widely used for CyanoHAB monitoring in lakes (Kim et al., 2020; Mu et al., 2021). Based on effective processing methods (Hu, 2009; Chen et al., 2019), satellite-based CyanoHAB products can be quickly obtained. However, optical satellite remote sensing cannot provide CyanoHAB information in a fully timely manner due to factors such as cloud cover, precipitation, and relatively coarse spatial resolution. Especially in local sensitive areas such as drinking-water sources, the demands of emergency monitoring cannot be met (Qiu et al., 2022).

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Drone and ground-based methods, including unmanned aerial vehicles (UAVs) and video devices (Kwon et al., 2020; Wang et al., 2023b), have emerged as effective solutions to overcome the limitations of satellite-based monitoring of CyanoHABs. These methods offer advantages by avoiding the frequency and spatial resolution limitations associated with satellite monitoring (Cook et al., 2023). Spectral indices have been widely employed as the predominant technique for CyanoHAB detection in digital images (Wu et al., 2019; Kislik et al., 2018), while computer vision and deep learning-based approaches have also shown promise (Wang et al., 2023b). However, these techniques require rectified and calibrated images with minimal environmental disturbances for optimal performance. Although these methods have enabled preliminary continuous and emergency monitoring of CyanoHABs in key areas and core positions, their precision is hindered by the heterogeneity of CyanoHABs, frequent changes in camera poses, and challenges in distinguishing CyanoHABs from shadows and turbid water bodies (Ma et al., 2022; Tan et al., 2023). Specifically, comprehensive CyanoHAB information covering the entire lake, key areas, and core positions cannot be obtained frequently.

Understanding the current state of CyanoHABs is crucial for predicting their spatiotemporal trends and developing proactive response strategies (Brookfield et al., 2021). Earlier, statistical models were predominantly used for CyanoHAB prediction (Summers and Ryder, 2023). These models established correlations between cyanobacterial biomass, meteorological factors, nutrient concentrations, and hydrodynamic parameters through experimental analysis (Freeman K., 2000; Xu et al., 2002). Studies have shown a close relationship between CyanoHAB occurrence and key water quality parameters, such as Chl-a and total phosphorus (TP) (Shahriar and Rahman, 2013; Peng et al., 2020). Thus, accurately predicting these parameters indirectly enables CyanoHAB prediction. However, these data-driven models have simple structures and convenient applications but lack a comprehensive understanding of lake ecosystems, resulting in inherent uncertainty, especially for short-term predictions (Pan et al., 2022). On the other hand, process-oriented ecological dynamic models, such as PCLake, AQUATOX, WASP, EFDC, and MIKE, accurately simulate the growth-drift-accumulation process of CyanoHABs by considering physical and chemical processes of cyanobacteria evolution (Hu et al., 2016, 2020; Li et al., 2018; Wu and Xu, 2011; Zhao, 2015). These models offer clear advantages, particularly for short-term CyanoHAB predictions (Summers and Ryder, 2023). However, their stringent data requirements pose challenges due to limited data acquisition capabilities in lakes. Enhancing the accuracy of these models can be achieved by incorporating assimilation modules for satellite-based CyanoHAB products (Wang et al., 2018). Additionally, the development of UAV remote sensing, video monitoring, and in-situ monitoring has significantly improved the monitoring of lake water environments, theoretically enabling accurate CyanoHAB prediction (Kwon et al., 2020; Wang et al., 2023b; Yang et al., 2019). However, there is currently a lack of efficient frameworks for integrating multi-source monitoring data to predict CyanoHABs.

One drawback of traditional CyanoHAB prediction models, including both data-driven and process-oriented approaches, is that their predictive outcomes often deviate from the practical requirements of CyanoHAB prevention and management (Qiu et al., 2022; Wang et al., 2023b). Following their occurrence, CyanoHABs tend to accumulate in nearshore regions, which can potentially lead to secondary disasters (Qian et al., 2022; Wang et al., 2023b). This poses significant threats to drinking water safety since water intakes are typically situated in these nearshore areas. Therefore, compared to other regions, monitoring CyanoHAB trends in nearshore areas becomes more critical. However, traditional models have not adequately addressed this need as they primarily focus on large-scale CyanoHAB trends, such as throughout an entire lake or extensive lake areas, often overlooking the risks associated with CyanoHAB accumulation in nearshore regions.

In this study, we have developed an integrated framework for collaborative monitoring and accurate prediction of CyanoHABs, which we have applied to Lake Chaohu. Initially, we established a monitoring network that integrates various approaches, referred to as the space-aerial-ground collaborative monitoring network in this paper. This network combines satellite observations, UAVs, video devices, in-situ systems, and field measurements to comprehensively assess CyanoHAB conditions. Furthermore, we employed high-precision simulations of the growth-drift-accumulation process of CyanoHABs to predict potential risks associated with CyanoHAB accumulation in nearshore areas. To the best of our knowledge, this is the first successful integration of space, aerial, and ground-based methods for CyanoHAB research in a lake. Given the global issue of eutrophication in lakes, this study can provide valuable guidance for the prevention, control, and emergency response of CyanoHABs in eutrophic lakes.

2. Materials and methods

2.1. Study area

This study focuses on Lake Chaohu (Fig. 1), the fifth largest freshwater lake in China. Situated in the central region of Anhui Province, Lake Chaohu (31°25′28″–31°43′28″N, 117°16′54″–117°51′46″E) is among the three significant lakes in China that require eutrophication control. This lake plays a crucial role in providing water for the city, controlling flooding, facilitating irrigation, and supporting fisheries and tourism industries. In recent years, with a population explosion and the rapid development of industrial and agricultural production in the watershed, the nutritional level of Lake Chaohu remained stubbornly high. The occurrence of CyanoHABs, largely attributed to lake eutrophication, has become a significant constraint on the sustainable development of regional socio-economic growth. Traditional CyanoHAB monitoring methods in Lake Chaohu rely mainly on satellite remote sensing and field measurement, which cannot provide timely assessment of CyanoHAB status that covers the entire lake, its key areas, and core positions. Consequently, conventional methods were limited in their capacity to offer scientific decision-making support for CyanoHAB prevention and control.

2.2. Various CyanoHAB monitoring means

Like most eutrophic lakes, the CyanoHAB monitoring means in Lake Chaohu include satellite remote sensing, UAV monitoring, video monitoring, in-situ monitoring and field measurement. However, each single method cannot meet the multi-scale monitoring requirement of CyanoHABs, i.e., covering the entire lake, its key areas, and core positions (Table 1).

(i) Satellite remote sensing can regularly obtain both the area and spatial distribution of CyanoHABs in the entire lake. In this paper, the floating algae index (FAI) index (Hu, 2009) was used to extract CyanoHABs from satellite images of Terra/Aqua MODIS, Sentinel-2 MSI and GOCI. The threshold value of 0.0006, employed to distinguish between intense blooming and non-bloom pixels, was in accordance with the methodology outlined in existing research (Li et al., 2017). Moreover, a machine learning algorithm-random forest (RF) (Shen et al., 2020, 2022) were also utilized to invert key water quality parameters such as Chl-a concentration and transparency.

(ii) UAV monitoring applies to emergency CyanoHAB monitoring in key areas such as water sources. In this paper, UAVs were used to collect digital images of target lake areas in emergency situations, and the collected images were then processed by image processing algorithms (the same method as shown in Fig. 2). Finally, CyanoHAB status was obtained in target lake areas, i.e., areas and coverages.

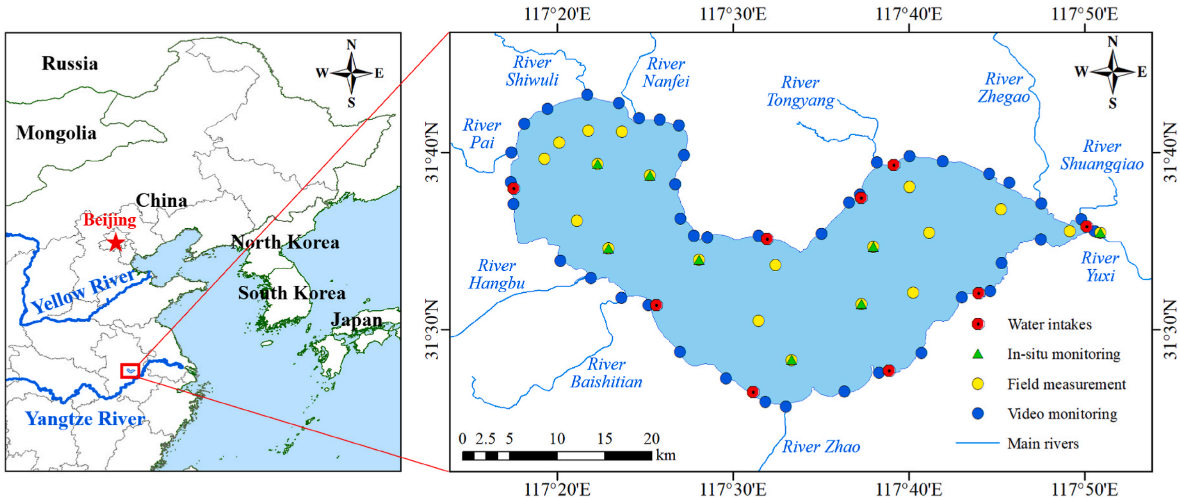

Fig. 1. The basic situation of Lake Chaohu. There are 20 field measurement positions, and eight of them are overlapped with in-situ monitoring systems. And there are 20 in-situ monitoring systems of 3D lake flow and 20 meteorological stations, the positions of which are overlapped with field measurement positions.

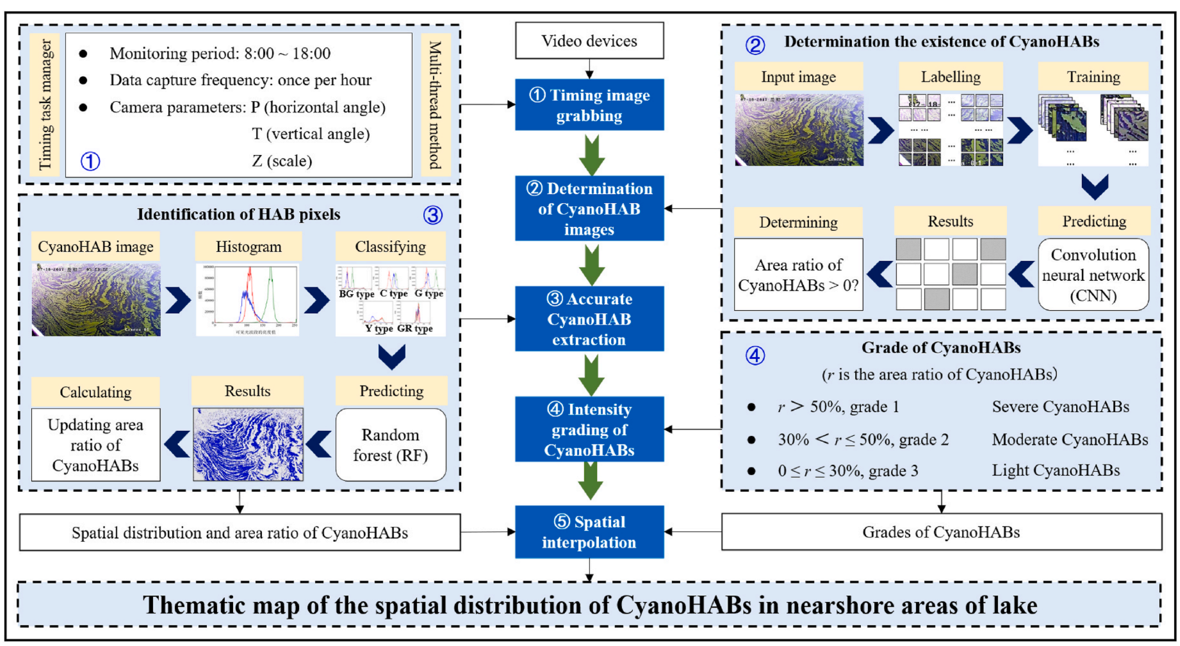

Fig. 2. Automatic monitoring method for cyanobacterial harmful algal blooms (CyanoHABs) in nearshore areas of Lake Chaohu utilizing land-based video monitoring systems.

(iii) Video monitoring can assess CyanoHAB conditions in key nearshore areas frequently and automatically. After occurrence, CyanoHABs easily accumulate in nearshore areas, often causing secondary disasters and threatening the water quality safety of water sources. Therefore, timely CyanoHAB monitoring in nearshore areas is essential for emergency CyanoHAB prevention and control. Video devices can work continuously and automatically without artificial participation under appropriate lighting. To overcome the inconsistent observation angles of video devices, based on the characterization analysis of CyanoHABs in video images, lighting intensities and background conditions of different video devices, CyanoHAB pixels were distinguished from CyanoHAB-free pixels using a multi-scale deep network and the random forest method (Fig. 2).

(iv) In-situ systems automatically monitored key water quality parameters of eight core positions (Fig. 1) once every 4 h and provided data support for water quality status analysis and CyanoHAB prediction.

(v) Field measurement was used to regularly monitor key water quality parameters of twenty core positions (Fig. 1) (once per month). During CyanoHAB outbreak periods (from Apr. 1 to Oct. 31 every year), the monitoring frequency was increased to twice per week. By this approach, emergency monitoring was conducted as needed, providing data support for CyanoHAB analysis and prediction.

2.3. Multi-scale CyanoHAB simulation and prediction

2.3.1. Construct a 3D hydrodynamic-water quality-algae coupled model

A 3D hydrodynamic-water quality-algae coupled model of Lake Chaohu was developed to realize the precise simulation and early warning of CyanoHABs (Fig. 3). The model began with the hydrological simulation of Lake Chaohu watershed. Ten hydrological stations were

Table 1
Analysis of advantages and disadvantages of single methods for CyanoHAB monitoring in Lake Chaohu.

Means	Monitoring results	Advantages	Disadvantages
Satellite remote sensing	(i) Monitoring region: the entire lake, (ii) monitoring indicators: CyanoHAB area and distribution, key water quality parameters, (iii) monitoring frequency: twice a day (Terra/Aqua MODIS), eight times a day (GOCI) and once every five days (Sentinel-2 MSI), and (iv) image resolution: 250 m (MODIS), 500 m (GOCI) and 10 m (Sentinel-2 MSI).	High monitoring frequency.	(i) Greatly affected by cloudy and rainy weathers, making it impossible to satisfy emergency monitoring requirements, and (ii) cannot accurately monitor CyanoHABs in key areas and core positions due to the limitation of spatial resolutions of images
UAV monitoring	(i) Monitoring region: key nearshore areas and core positions, (ii) monitoring indicators: CyanoHAB coverage, and (iii) monitoring frequency: dynamically determined based on exceeding-standard situations of CyanoHAB monitoring and prediction.	Strong flexibility, low-altitude flight, and high resolution of images	(i) Difficult to achieve large-scale or daily monitoring, due to the limited navigating ability of UAVs and the required professional participation, and (ii) require ideal weather conditions for on-site operation, e.g., no wind or breeze, no rain, etc.
Video monitoring	(i) Monitoring region: key nearshore areas, (ii) monitoring indicators: CyanoHAB coverage, and (iii) monitoring frequency: hourly from 8 a.m. to 6 p.m. every day.	High monitoring frequency.	(i) Susceptible to interference from factors such as solar flares and shore vegetation, (ii) CyanoHAB status in the entire lake cannot be fully defined, and (iii) cannot obtain specific water quality parameters.
In-situ monitoring	(i) Monitoring region: core positions, (ii) monitoring indicators: TN, TP, COD, NH_3-N, water temperature, Chl-a, DO, pH, conductivity and BOD, and (iii) monitoring frequency: once every 4 h.	High monitoring frequency, and detailed monitoring indicators.	Cannot obtain the integrated CyanoHAB information that covers the entire lake, its key area, and core positions.
Field measurement	(i) Monitoring region: core positions, (ii) monitoring indicators: TN, TP, COD, NH_3-N, water temperature, Chl-a, DO, pH, conductivity and BOD, and (iii) monitoring frequency: once a month (not in CyanoHAB prevention and control periods), twice a week (in CyanoHAB prevention and control periods) and dynamically determined (based on exceeding-standard situations).	High monitoring accuracy, and detailed monitoring indicators.	(i) Cannot obtain the integrated CyanoHAB information that covers the entire lake, its key area, and core positions, and (ii) the requirement of emergency monitoring cannot be met in prevention and control periods of CyanoHABs, due to the poor monitoring efficiency and high working cost.

deployed in 10 main rivers that flow into or out of Lake Chaohu (Fig. 1). The monitored indicators of these stations include water level, flow, and water volume. Based on these data, daily flows of the 10 rivers were simulated using the distributed hydrological model named Grid-Xinanjiang (Huang et al., 2018), providing boundary conditions for the hydrodynamic simulation of Lake Chaohu. Here, the Xinanjiang model grid size was set to 500 × 500 m, details of which can be seen in Huang et al. (2018).

Afterwards, we completed the hydrodynamic simulation of Lake Chaohu. The hydrodynamic conditions of Lake Chaohu were simulated based on the daily flows of ten main rivers and 3D lake flow monitoring results. Twenty in-situ systems were utilized, as depicted in Fig. 1. The monitored parameters included flow velocity and direction, with a monitoring frequency of once per day. The EFDC model was employed for this simulation, with a grid size set to 500 × 500 m. This grid was vertically divided into two layers, with a roughness height at the bottom of 0.02 m and a time step of 200 s.

The meteorological data used was observed hourly by 20 meteorological stations deployed in Lake Chaohu (Fig. 1). The observed meteorological factors included wind speed, wind direction, temperature, precipitation, evaporation and solar radiation. The boundary conditions of the model used include the flows of the 10 main rivers, details of which can be seen in Huang et al. (2018).

Finally, we realized the hourly CyanoHAB prediction, both the CyanoHAB trends in the entire lake and the accumulation risks of CyanoHABs in nearshore areas. For this purpose, four indices were constructed, i.e., algal bloom index, lake shoreline index, hydrodynamic index, and wind direction index. These indices were based on the assimilation of space-aerial-ground collaborative monitoring data, hourly weather forecast data, hydrodynamic simulation results of Lake Chaohu, and high-frequency monitoring data pertaining to water quality and hydrology (Qian et al., 2022). In this study, the frequency of weather forecast data, CyanoHAB information gathered via video devices, and in-situ monitoring data pertaining to water quality and hydrology was set at 1 h. For other types of data, such as satellite-derived CyanoHAB products, they were adjusted to an hourly frequency through time series interpolation.

2.3.2. Drive the hydrodynamic-water quality-algae coupled model

The driving dataset of the constructed model was dynamically generated (Fig. 3) based on: (i) high-frequency monitoring data of the space-aerial-ground collaborative network, (ii) meteorological data from the 20 automatic monitoring stations in the lake (monitoring data) and Hefei Meteorological Bureau (forecast data), (iii) hydrological monitoring data from the 10 hydrological automatic monitoring stations of the 10 main rivers around the lake, (iv) 3D digital flow field data by interpolation of monitoring data from the 20 in-situ monitoring systems in the lake, and (v) shoreline and underwater 3D terrain data from the Anhui Provincial Lake Chaohu Administration. The simulated indicators included TN, TP, DO, COD, Chl-a, surface algal biomass, NH_3-N, and CyanoHAB accumulation risks in nearshore areas.

The initial distribution of CyanoHABs across the entire lake is a critical factor in predicting their spread. The accuracy of this initial state directly impacts the precision of the model's predictions. Current research often uses satellite-based remote sensing images to generate this initial state, but this method fails to account for CyanoHAB distribution in key local areas such as water sources. In contrast, this study proposes the use of additional data sources. These include the areas and coverages of CyanoHABs in target lake areas monitored by UAVs, and the conditions of CyanoHABs in key nearshore areas assessed by video devices. By incorporating this multi-source CyanoHAB information, we can improve the accuracy of the initial conditions for CyanoHAB prediction, thereby enhancing the overall prediction accuracy.

2.3.3. Evaluate model performance

The accuracy of the constructed model was verified using collaborative CyanoHAB monitoring data. Initially, the accuracy of CyanoHAB prediction in the entire lake was verified by the 20 in-situ monitoring systems in the lake. As CyanoHABs cannot be directly monitored by in-situ systems, a popular CyanoHAB characterization factor in water bodies, i.e., Chl-a, was employed as the indicator of accuracy verification. Furthermore, three water quality parameters (TN, TP, and NH_3-N) were utilized as supplementary indicators for accuracy verification.

Additionally, the accuracy of CyanoHAB accumulation prediction in nearshore areas was jointly verified through video-based and satellite-based monitoring results. For water areas with high predicted CyanoHAB accumulation risks, the actual CyanoHAB accumulation situation

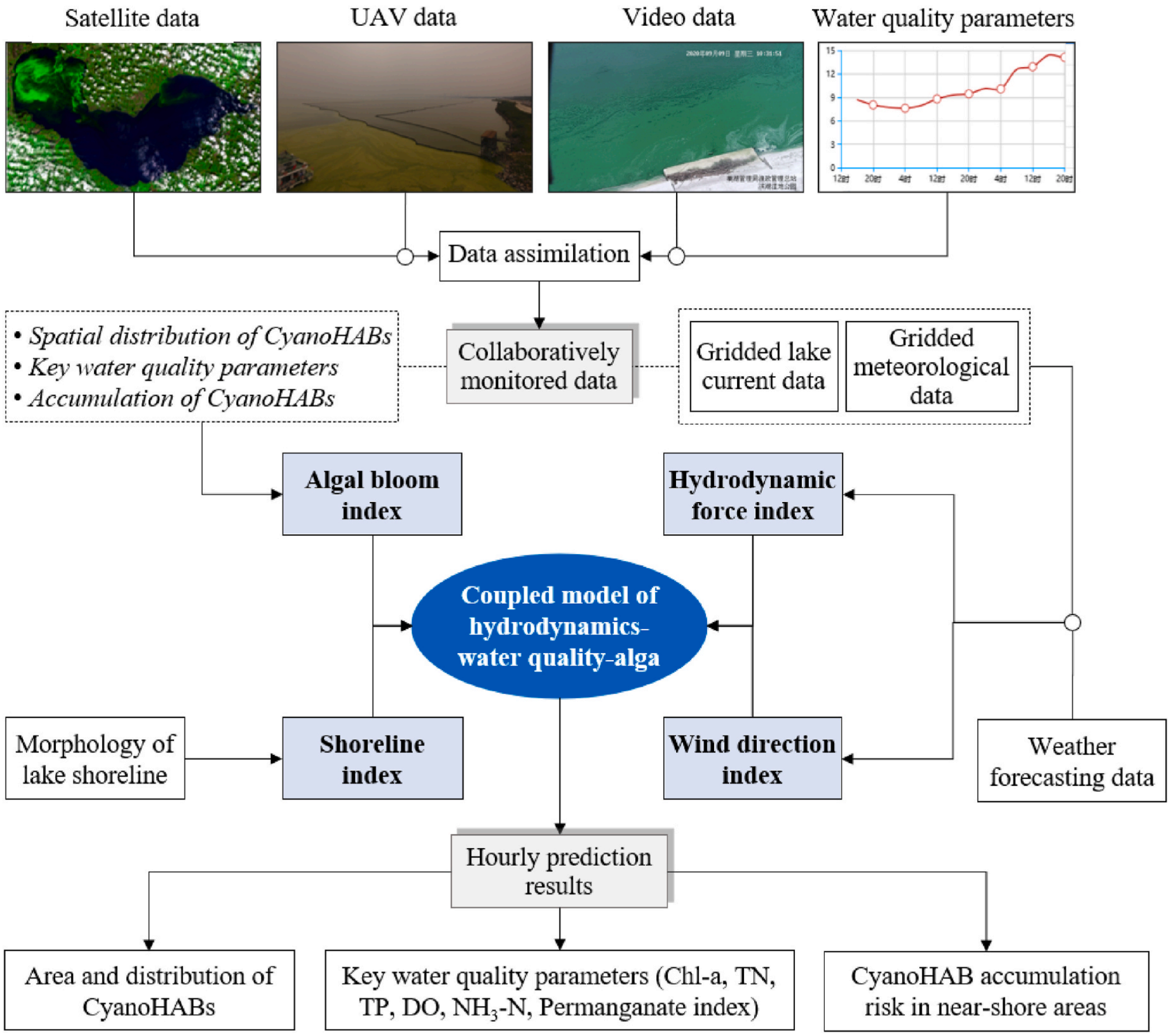

Fig. 3. The process of multi-scale CyanoHAB simulation and prediction.

(e.g., range and intensity) was verified by a nearby land-based video device. Moreover, satellite-based Chl-a products were used as supplementary data to verify the simulated CyanoHAB accumulation risks in nearshore areas, i.e., to determine whether the Chl-a concentrations in water areas with high predicted CyanoHAB accumulation risks were significantly higher than those in other water areas.

3. Results

3.1. Space-aerial-ground collaborative monitoring of CyanoHABs

Fully automatic CyanoHAB extraction has been achieved based on multi-source satellite images. Moreover, the CyanoHAB status in Lake Chaohu can be evaluated in a timely manner on sunny days (Fig. 4a). The accuracy verification results are shown in Fig. 6a. In local sensitive water areas, particularly where high-frequency CyanoHAB monitoring is not feasible via satellites, emergency monitoring was effectively executed by UAVs (Fig. 4b), and the accuracy verification results are shown in Fig. 6b. For nearshore areas that are more prone to CyanoHAB accumulation and consequently pose a significant concern in lake water environment management, 42 sets of land-based video devices were used to frequently monitor CyanoHABs and the whole process was implemented in an unattended manner. From 8 a.m. to 6 p.m. every day, CyanoHABs were hourly monitored in key nearshore areas (Fig. 5), and the accuracy verification results are shown in Fig. 6c.

Furthermore, timely assessment of the current status, exceptional situations, and trends in water quality at core positions was realized via in-situ systems and field measurements. Among the indicators obtained, TP and NH_3-N proved particularly valuable for the analysis and judgment of CyanoHAB condition throughout the lake.

Finally, by integrating multiple monitoring means, a space (satellite)-aerial (UAV)-ground (video device, in-situ system and field measurement) collaborative CyanoHAB monitoring network was constructed (Fig. 7). As a result, integrated monitoring of CyanoHABs was achieved, covering the entire lake, its key areas, and core positions. Accordingly, the current status and exceeding-standard situation about CyanoHABs and key water quality parameters can be quickly understood (Fig. 8), accelerating the scientific management and emergency control of CyanoHABs. In this collaborative monitoring network, satellites, in-situ systems, and video devices are daily monitoring means, which were automatically activated at regular times every day; UAVs and field measurements are emergency monitoring means which were activated in case of abnormal situations, e.g., exceeding-standard water quality, abnormal water color, CyanoHAB accumulation, etc.

3.2. Simulation and prediction of CyanoHABs

CyanoHABs and key water quality parameters were simulated and predicted hourly for the next seven days in this research, and the prediction indicators included TN, TP, DO, COD, NH_3-N, Chl-a, surface algal

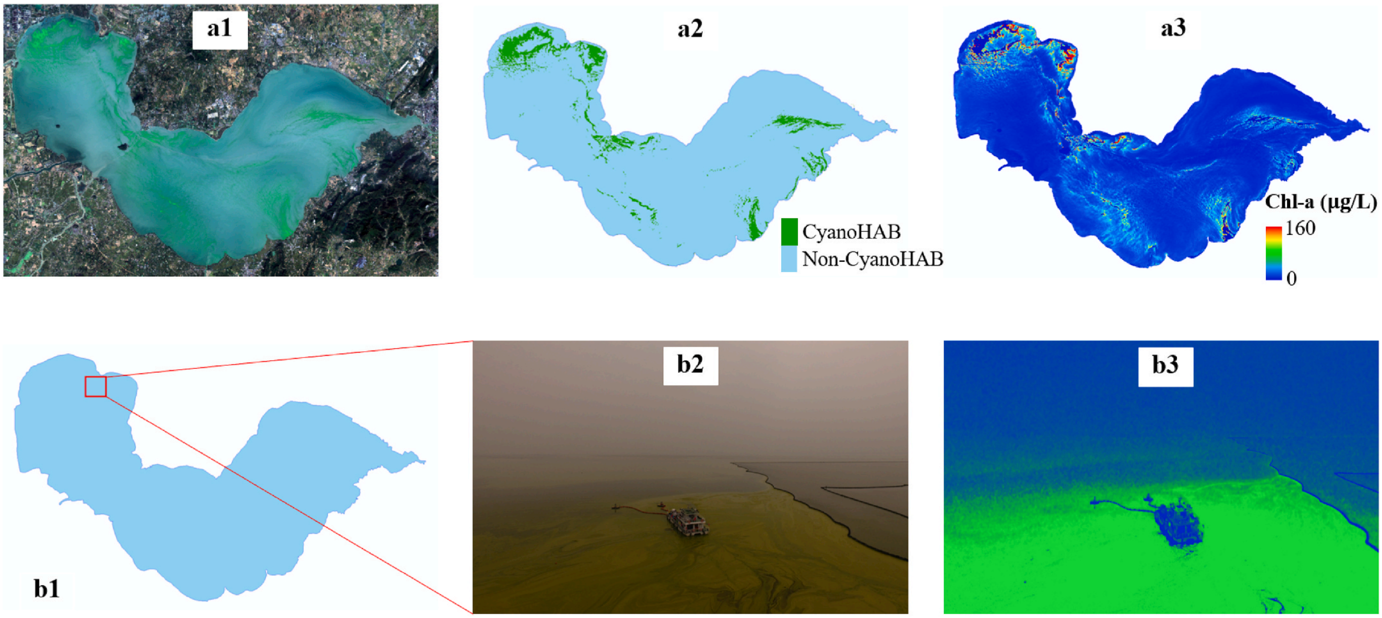

Fig. 4. CyanoHAB monitoring results by satellite and UAV. (a1) is the original satellite image with Sentinel-2 MSI as data source (the imaging date is Sep. 17, 2022), and (a2) and (a3) are results of CyanoHAB extraction (the CyanoHAB area is 6.51 km^2) and Chl-a inversion, respectively. The region in the red box in (b1) denotes the water area of UAV monitoring, (b2) is the on-site image collected by UAV, and (b3) is the CyanoHAB extraction result of (b2) (green pixels represent CyanoHAB, blue pixels stand for non-CyanoHAB, and the area ratio of CyanoHABs is 59.24%).

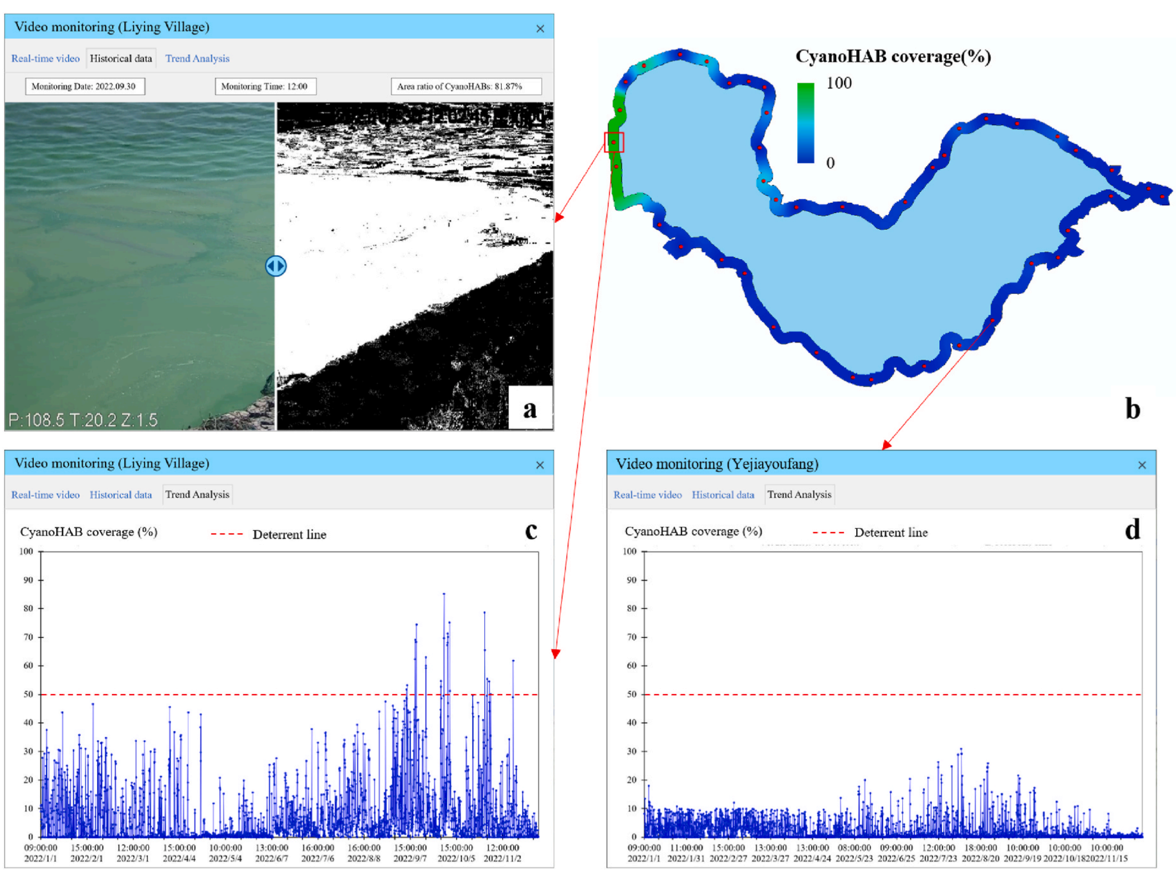

Fig. 5. Video-based CyanoHAB monitoring results in nearshore areas. (a) CyanoHAB extraction results (area ratio) of the station named Liying Village, (b) spatial distribution of CyanoHAB intensity in nearshore areas, (c) long-term CyanoHAB monitoring results (area ratio) of the station named Liying Village, and (d) long-term CyanoHAB monitoring results (area ratio) of another station named Yejiayoufang.

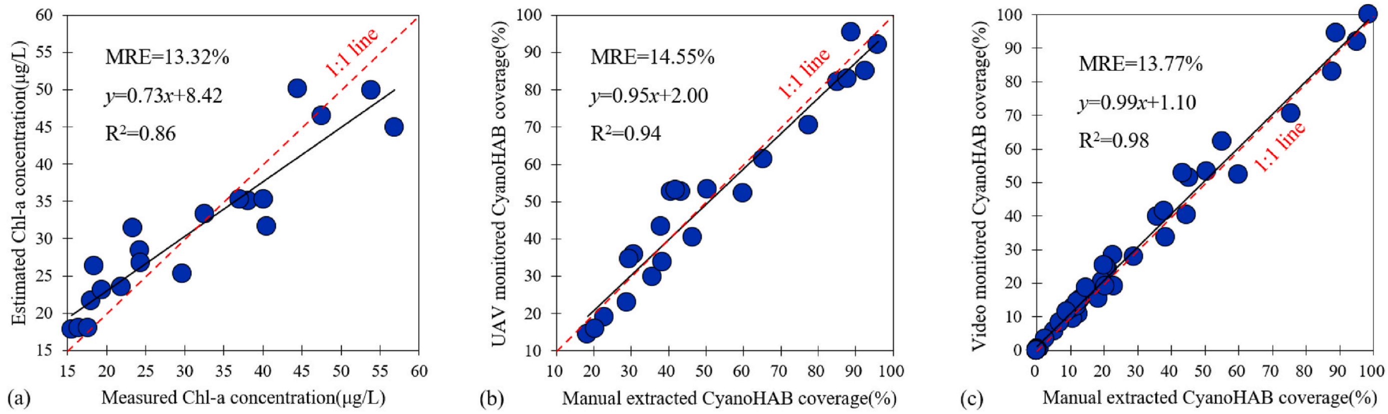

Fig. 6. Accuracy verification results of satellite-based, UAV-based, and video-based CyanoHAB monitoring. (a) presents the accuracy verification results of satellite-based monitoring. The study utilized 20 sets of validation data, wherein estimated Chl-a concentrations were derived from Aqua/Terra MODIS data, while measured Chl-a concentrations were obtained through field measurements. (b) illustrates the accuracy verification outcomes of UAV-based monitoring. This segment involved 20 sets of validation data, wherein UAV-monitored and manually extracted CyanoHAB coverages were calculated based on digital images captured by UAVs, utilizing the specifically designed image processing algorithm and manual methods, respectively. (c) depicts the accuracy verification results of video-based monitoring. This section encompasses 42 sets of validation data, wherein video-monitored and manually extracted CyanoHAB coverages were computed based on digital images captured by video devices, employing the purposefully designed image processing algorithm and manual techniques, respectively.

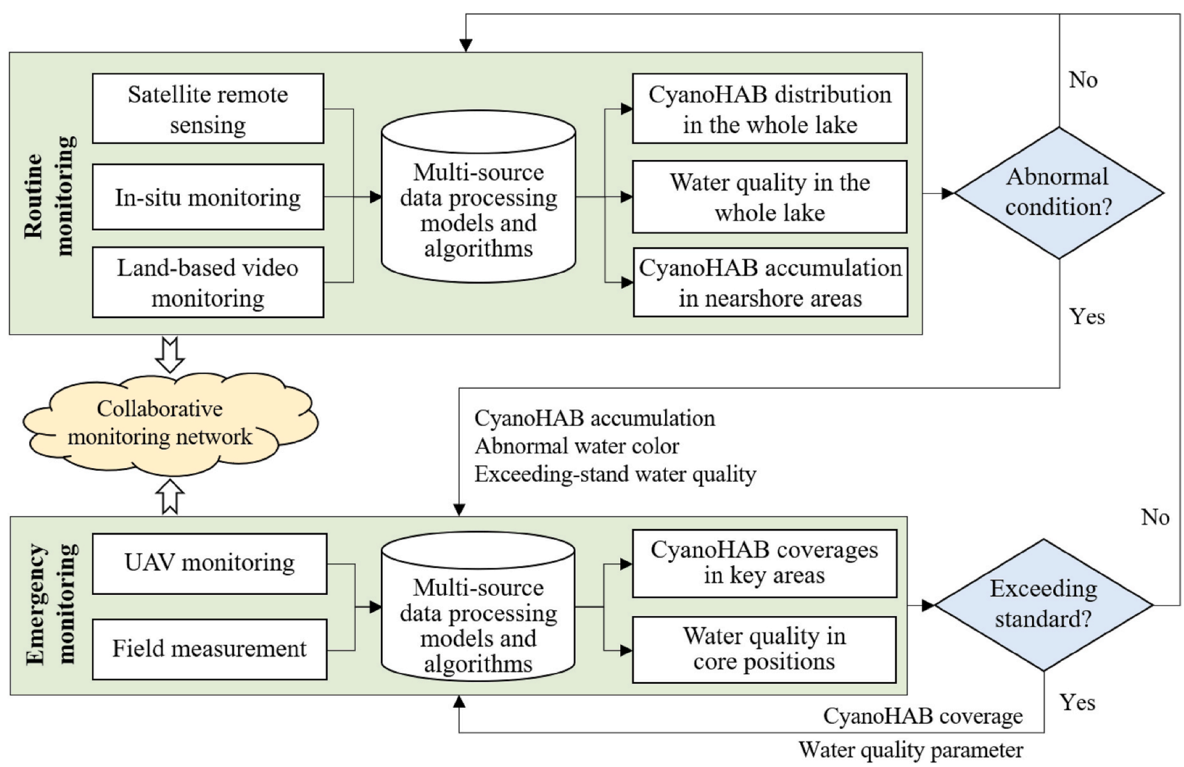

Fig. 7. Working mode of the space-aerial-ground collaborative CyanoHAB monitoring network.

biomass and the probability of a CyanoHAB outbreak. Taking Chl-a as an example, the predicted results are shown in Fig. 9a. Additionally, the quantitative evaluation of CyanoHAB accumulation risks in nearshore areas and their spatiotemporal trends were achieved for the next seven days (Fig. 9b).

The accuracy of water quality prediction in the lake was evaluated using in-situ monitoring data. Taking the predicted results on Sep. 27, 2021 (spanning from Sep. 27 to Oct. 3) as an example, we compared the monitoring data of an in-situ system and the prediction results at the same position to validate accuracy. The chosen indicators for this validation were Chl-a, TN, TP and NH_3-N. Our findings (Fig. 10) suggest that: (i) the model's accuracy is high overall and the prediction results in the next 1–3 days are reliable, (ii) the errors of prediction tend to increase as the simulation period extends, and (iii) among the four validation indices, Chl-a exhibited the highest simulation precision; TN and TP demonstrated comparable accuracies, and NH_3-N had the lowest accuracy.

Moreover, the prediction accuracy of CyanoHAB accumulation risks in nearshore areas was evaluated by video-based and satellite-based monitoring (Fig. 11). The monitoring results by 42 land-based video devices were used to verify the CyanoHAB accumulation situation in those nearshore areas with high predicted CyanoHAB accumulation risks (Fig. 11a). Additionally, the prediction results of CyanoHAB accumulation were compared with satellite-based monitoring

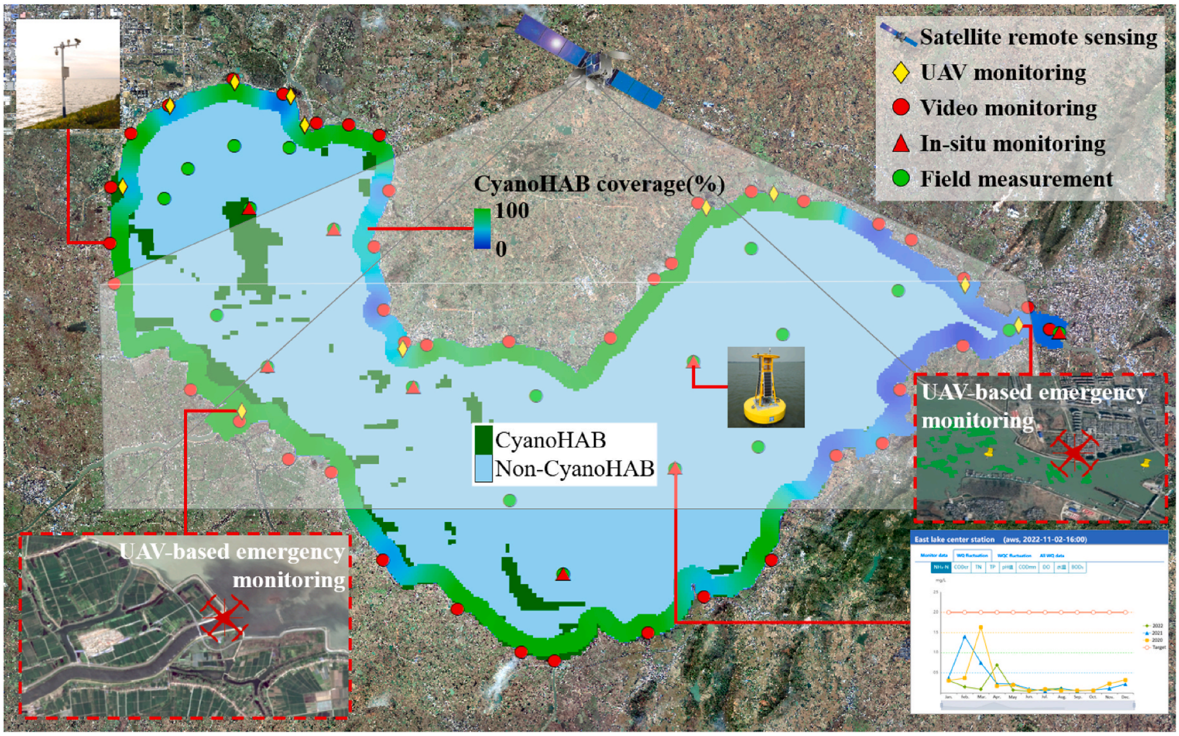

Fig. 8. The space-aerial-ground collaborative CyanoHAB monitoring results. Integrated CyanoHAB information was acquired simultaneously, which provides CyanoHAB area and distribution covering the entire lake, its key areas, and core positions.

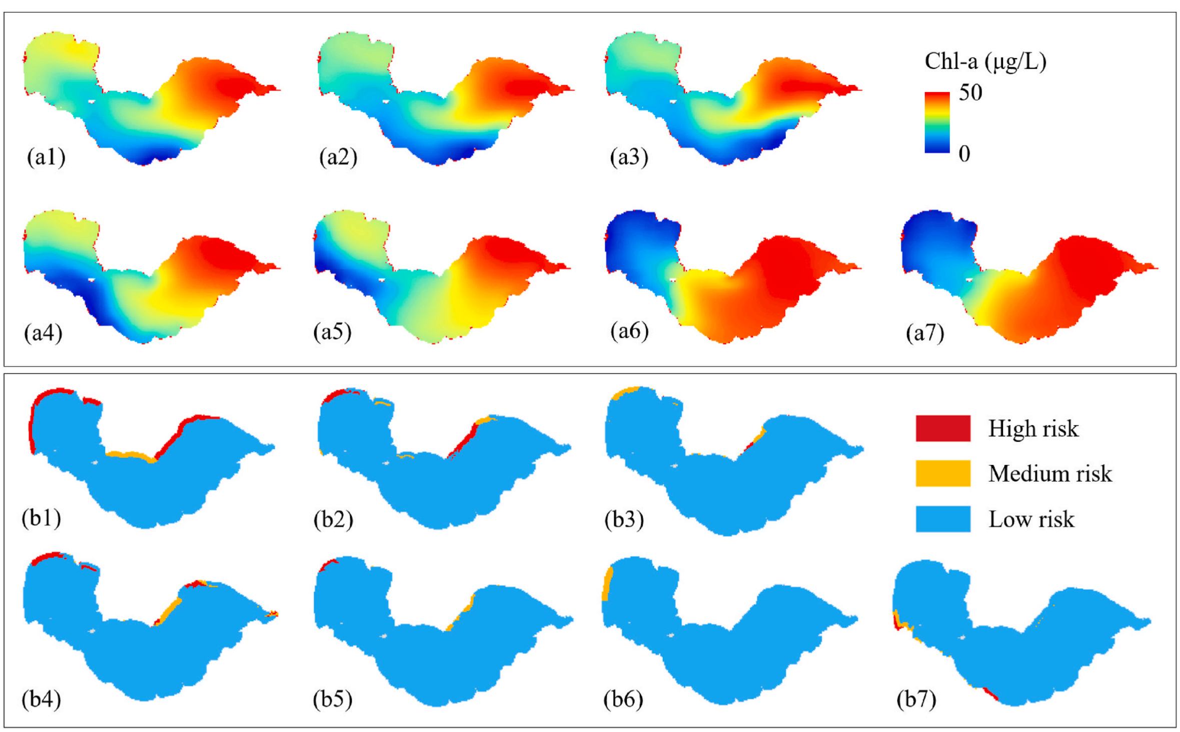

Fig. 9. Prediction results of Chl-a and CyanoHAB accumulation in the future seven days. (a1)~(a7) are the prediction results of Chl-a for the next 1–7 days, respectively. (b1)~(b7) are the prediction results of CyanoHAB accumulation in nearshore areas in the next 1–7 days, respectively. Note that the time resolution of the original prediction results is 1 h and the daily prediction results here are the average values calculated based on the hourly prediction results of every day.

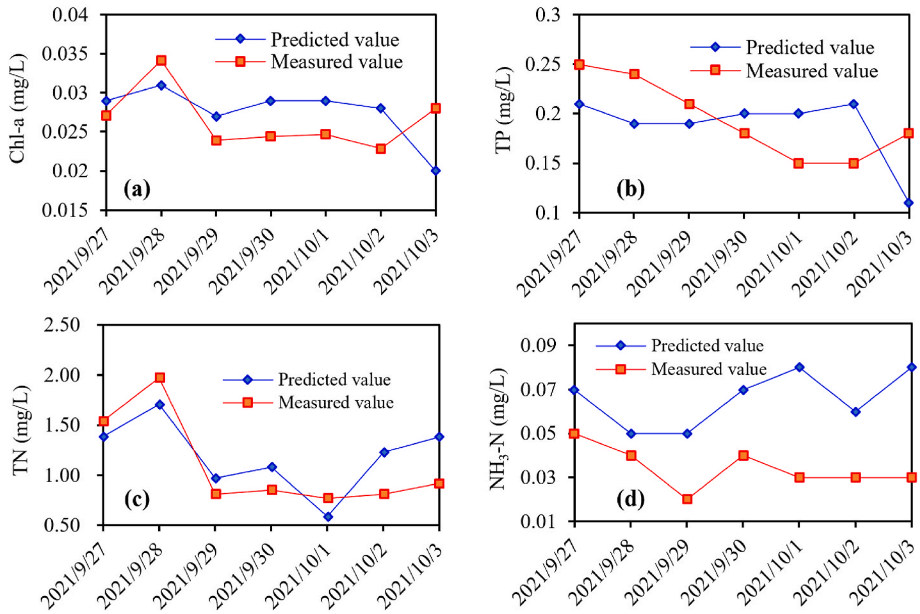

Fig. 10. Accuracy verification results of water quality parameter prediction. The measured water quality parameters are sourced from an in-situ monitoring system.

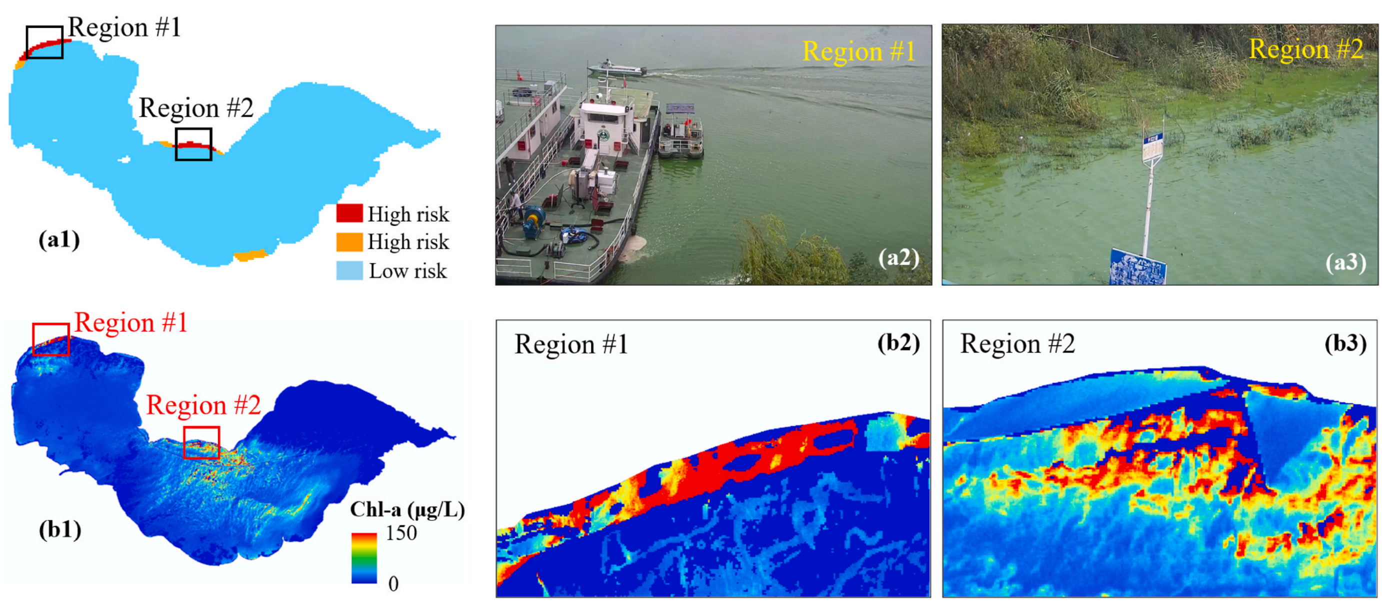

Fig. 11. An example of the application of the developed framework. (a1) predicted results of CyanoHAB accumulation in nearshore areas (Oct. 19, 2019) with 250 × 250 m grid for each unit, (a2) and (a3) on-site images in Region #1 and Region #2 in (a1) which were captured by land-based video devices; (b1) inverted spatial distribution of Chl-a based on Sentinel-2 MSI image data (Oct. 19, 2019), and (b2) and (b3) partial enlarged views of Region #1 and Region #2 in (b1).

(Fig. 11b), which showed high prediction accuracy.

4. Discussion

4.1. Advantages of developed framework

The frequency and scale of CyanoHABs in lakes increase continuously at present (Huisman et al., 2018; Cook et al., 2023). Timely evaluation of CyanoHAB status and accurate prediction of their spatio-temporal tends are of great significance for scientific prevention and control of them. However, traditional methods cannot satisfy this demand. This paper presents an integrated framework for the collaborative monitoring and precise prediction of CyanoHABs, which has been applied in practice in Lake Chaohu. This framework has achieved significant breakthroughs in enhancing both the monitoring coverage and the prediction precision of CyanoHABs. First, compared to single monitoring, this framework achieved the collaborative CyanoHAB monitoring that covers the entire lake, its key areas, and core positions, enabling a thorough understanding of current status and any abnormal information related to CyanoHABs (Fig. 8). Furthermore, the conventional simulation model for CyanoHABs in lakes was enhanced and multi-scale CyanoHAB prediction was achieved, interconnecting the entire lake and its nearshore areas (Fig. 9). Under the conditions of limited emergency response resources, this framework has important guiding significance for emergency prevention and control of CyanoHABs in lakes.

On Sep. 29, 2021, the MODIS/Aqua image data indicated that the total algae volume in the eastern, central, and western areas of Lake

Chaohu were 256.5 t, 199.9 t, and 244.6 t, respectively. The CyanoHAB prediction results in the entire lake indicated high Chl-a concentrations in the eastern, central, and western areas the following day (Fig. 12a1). The highest concentration was observed in the eastern area. This indicated a high risk of CyanoHAB outbreaks throughout the lake the following day. Notably, the eastern area exhibited a higher risk compared to both the eastern and central areas. The simulation results also indicated that the areas with high CyanoHAB accumulation risks the following day were mainly located in the eastern and northwestern areas (Fig. 12a2).

On Sep. 30, 2021, unsurprisingly, a large-scale CyanoHAB occurred in Lake Chaohu. The satellite-based CyanoHAB result (Fig. 12b1) indicated that the CyanoHAB areas in the eastern, central and western regions were 133.41 km^2, 71.04 km^2 and 62.70 km^2, respectively. This was consistent with the prediction results (Fig. 12a1). The video-based CyanoHAB monitoring results (Fig. 12b2) showed that the areas with higher CyanoHAB intensities were mainly located in the eastern, southeastern and northwestern nearshore areas, which was consistent with the satellite-based results (Fig. 12b1) and the prediction results (Fig. 12a2).

Based on the prediction results of CyanoHAB accumulation in nearshore areas (Fig. 12a2), the occurrence of CyanoHABs in several key nearshore areas was monitored by UAV on Sep. 30, 2021. The results (Fig. 13) showed that CyanoHABs occurred in several water areas with high predicted accumulation risks; thus, the simulation results were consistent with the actual situations.

The Lake Chaohu application effectively illustrates the advantages of the integrated framework presented in this paper. An innovative collaborative CyanoHAB monitoring network was established, capable of effectively supplementing CyanoHAB monitoring in the absence of viable satellite data. By placing land-based video devices around the lake, we were able to obtain both the intensity and distribution of CyanoHABs in key nearshore areas (Figs. 5 and 12b2), such as water intakes, in near real time. This provided scientific guidance for lake CyanoHAB inspections; thus, frontline workers were able to focus on several key areas rather than conduct comprehensive inspections as before. Accordingly, the work efficiency was greatly improved and the work costs were reduced. In abnormal situations, such as CyanoHAB occurrence, UAVs and field measurements were employed to conduct emergency monitoring in key areas and core positions. By efficiently combining various methods (Fig. 7), the shortcomings of each method were overcome, and multi-level integrated monitoring of CyanoHABs was achieved (Fig. 8).

Moreover, traditional CyanoHAB prediction methods in lakes (Zhang et al., 2013; Li et al., 2018; Brookfield et al., 2021) usually focused on predicting the risk and area of CyanoHABs in the entire lake or extensive lake areas. However, no effective strategies for emergency responses have been established in the day-to-day practice of large-scale CyanoHAB prevention and control (Shi et al., 2022). And with limited disposal resources, managers are more concerned about predicting CyanoHAB situations in key areas and core positions in nearshore areas, so as to develop response plans in advance and achieve optimal utilization of limited emergency disposal resources. Traditional methods, however, lacked the capacity to offer decision-making support in this domain. In contrast, the multi-scale simulation and prediction model constructed in this study not only predicts the trend of CyanoHABs in the entire lake (Figs. 9a and 12a1), but also foreknows their accumulation risks in nearshore areas, involving more decision-making significance for CyanoHAB prevention and control (Figs. 9b–11a and 12a2). This helps managers of lake water environments to anticipate CyanoHAB situations in key nearshore areas and core positions, which enables earlier deployment of emergency response resources (Fig. 11a2), reduces the potential impacts, and ensures water quality and ecological safety.

4.2. Framework deficiencies

Despite the significant advantages described in Section 4.1, some limitations remain in the developed framework. First, although we have preliminarily constructed a space-aerial-ground collaborative CyanoHAB monitoring network, large-scale CyanoHAB monitoring relies only on satellite remote sensing. This approach proves challenging when applied to smaller or medium-sized lakes.

Secondly, the use of UAVs has been instrumental in the developed framework for high-frequency CyanoHAB monitoring in key nearshore areas. However, this process necessitates on-site personnel to collect images and bring them back to the laboratory for processing and analysis. The efficiency of this approach is currently constrained by factors such as the round-trip time for personnel, on-site operational efficiency, and the level of automation in data processing. Consequently, there remains a substantial discrepancy between the automated data processing/monitoring capabilities and the actual demand for emergency prevention and control of CyanoHABs.

Furthermore, while we have made preliminary progress in multi-scale CyanoHAB prediction which interconnects the entire lake and its nearshore areas, there remains a gap in effective digital twin methods for full factors of the physical lake body. Key driving data for the

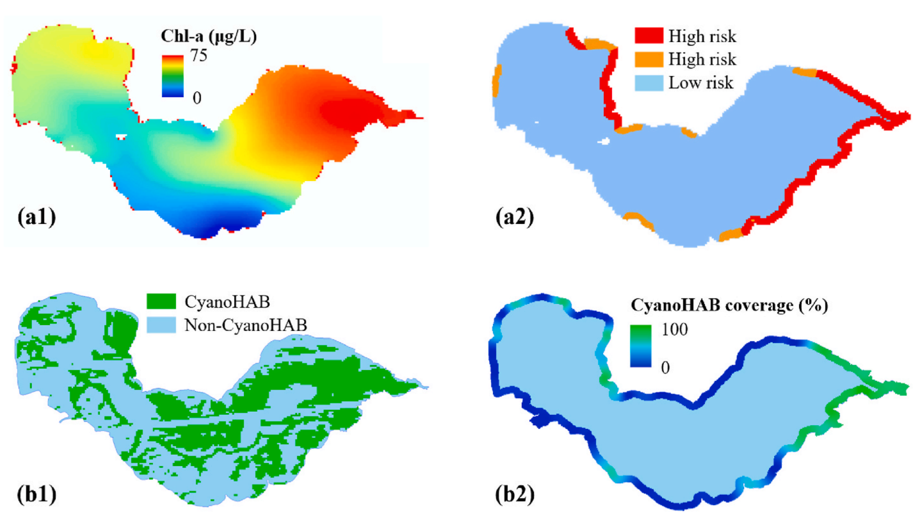

Fig. 12. CyanoHAB prediction and monitoring results on Sep. 30, 2021. (a1) and (a2) are prediction results of Chl-a distribution and CyanoHAB accumulation, respectively. (b1) and (b2) are the satellite-based (using Aqua MODIS data with a transit time approximately at 1 p.m.) and video-based (at 1 p.m.) CyanoHAB monitoring results, respectively.

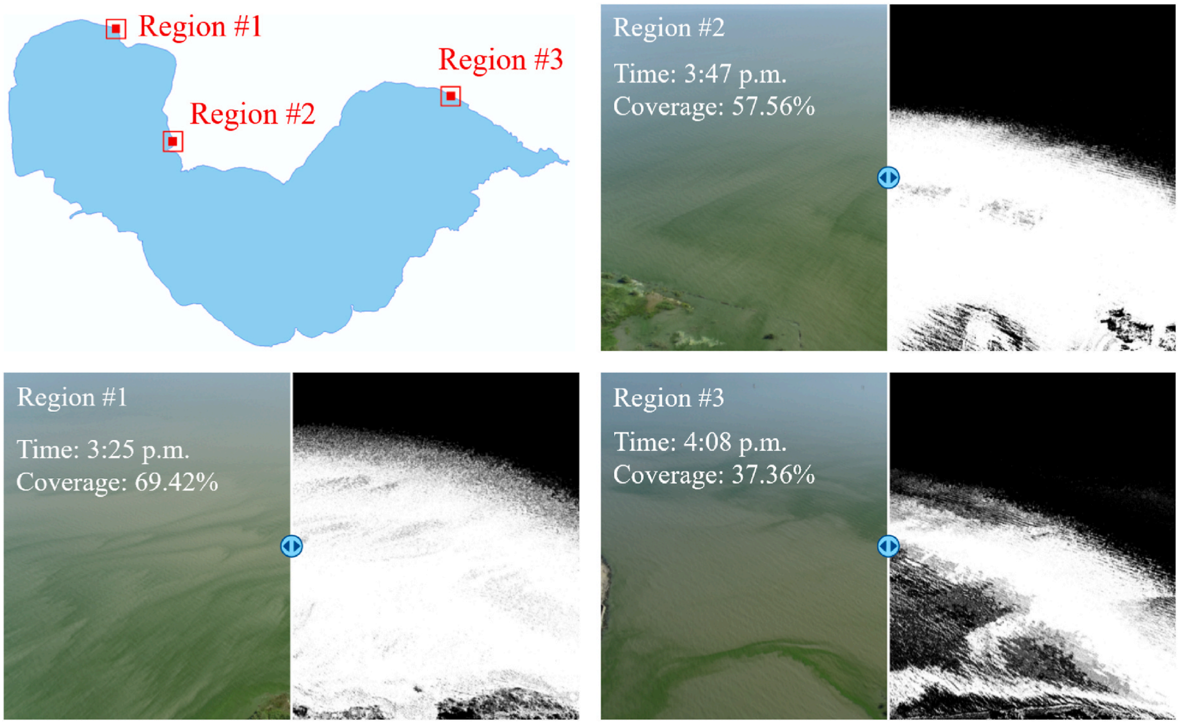

Fig. 13. UAV-based CyanoHAB monitoring results in three key water areas on Sep. 30, 2021.

CyanoHAB prediction model, e.g., rivers, underwater topographies vertical distribution characteristics of water quality and algae, etc., was all the generalizations of real geographic information. Accordingly, there is still some uncertainty in the prediction results, making it challenging to capture the full CyanoHAB process, i.e., growth, drift and accumulation. Consequently, there is significant potential for enhancement in supporting emergency preparedness and scientific prevention and control of CyanoHABs.

4.3. Future work

Lacustrine CyanoHABs, influenced by eutrophication, global warming and extreme climate conditions, are anticipated to persist for an extended period in the future (Huisman et al., 2018; Ho et al., 2019). The use of the developed framework has significant scientific importance and practical value for CyanoHAB prevention and management. Despite the promising application and performance of this framework, several infrastructure and strategic improvements are required for its widespread use.

First, it is imperative to enhance the integration and improvement of monitoring resources, including space, aerial, and ground-based remote sensing. For large lakes whose areas exceed 500 km^2, such as Lake Erie and Lake Taihu, space remote sensing data sources with low satellite revisiting periods and medium-to-high image resolutions are recommended, such as Terra/Aqua MODIS and Sentinel-3 OLCI. Conversely, for small-to-medium-sized lakes, it is advisable to utilize space remote sensing data sources with high image resolutions, such as TRMM VIRS and GF. To address the issue of absent satellite data due to adverse weather conditions, it is recommended to incorporate supplementary monitoring methods. These primarily encompass aerial remote sensing, particularly low-altitude and ground-based means, which includes land-based, tower-based, and platform-based remote sensing. By fusing and splicing multi-source remote sensing data, high-frequency CyanoHAB monitoring can be obtained in key lacustrine areas such as water sources and landscape areas.

Simultaneously, it is necessary to further improve the automation and collaboration of the monitoring-prediction process of CyanoHABs. CyanoHABs usually come and go without a trace (Zhang et al., 2021), which means that timeliness in CyanoHAB monitoring and prediction is crucial to their emergency prevention and control. The automation of satellite-based and video-based CyanoHAB monitoring was achieved in this research, but the UAV-based CyanoHAB monitoring still requires a large amount of manual participation. By building automatic airports for UAVs, routine inspection and emergency monitoring of CyanoHABs can be achieved in the near future.

Furthermore, it is imperative to develop in-situ observation systems for the lacustrine eco-environment. These systems should be capable of dynamically capturing the true condition of lake bodies, including water levels, spatial distribution of water quality parameters, 3D flow fields, underwater terrains, and the volume of water flowing into and out of the lake. On this basis, it will be possible to create a digital twin framework that accurately represents the lake body, enabling a CyanoHAB footprint simulation. In our research, there is an absence of digital twin methods that encompass all factors of a physical lake body. As it stands, the driving data for CyanoHAB simulation and prediction is all the generalizations of real geographic information, affecting the prediction accuracy. In the foreseeable future, advancements in technologies like digital twins and data assimilation will facilitate the creation of digital twins for lakes in the real world. This will enable high-precision calculations of hydrodynamic-water quality-algae coupled models and CyanoHAB footprint simulations.

5. Conclusions

An innovative framework has been developed for the collaborative monitoring and precise prediction of CyanoHABs in eutrophic lakes, specifically Lake Chaohu. This framework integrates various single means to create a multi-level integrated monitoring network, making the first time such a network has been constructed with a specific focus on a lake. The goals of rapid assessment of CyanoHAB status and intelligent identification of anomalies were achieved. On this basis, a hydrodynamic-water quality-algae coupled model was developed, innovatively interconnecting the entire lake and its nearshore areas for multi-scale CyanoHAB prediction. This framework can provide strong support for water source protection and drinking water safety assurance. The practical application case in Lake Chaohu has demonstrated the significant advantages of this framework. Furthermore, the limitations of this framework were thoroughly examined, and potential avenues for future research were highlighted to address these issues and further refine the framework in the near term.

CRediT authorship contribution statement

Yinguo Qiu: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Conceptualization. **Jiacong Huang:** Writing – original draft, Validation, Methodology, Data curation. **Juhua Luo:** Visualization, Methodology, Data curation. **Qitao Xiao:** Supervision, Resources, Methodology. **Ming Shen:** Validation, Investigation, Data curation. **Pengfeng Xiao:** Visualization, Validation, Methodology. **Zhaoliang Peng:** Methodology, Data curation. **Yaqin Jiao:** Validation, Investigation, Data curation. **Hongtao Duan:** Writing – review & editing, Supervision, Methodology, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yinguo Qiu reports financial support was provided by Nanjing Institute of Geography and Limnology Chinese Academy of Sciences. Yinguo Qiu reports a relationship with Nanjing Institute of Geography and Limnology Chinese Academy of Sciences that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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