Cyanobacterial blooms management: A treatment path optimization perspective

Ming Liu[1,a], Jiani Wu[1,b]

[1]School of Economics and Management, Nanjing University of Science and Technology, Nanjing, 210094, China

[a]Corresponding author e-mail: liuming@njust.edu.cn
[b]e-mail: 525838737@qq.com

Abstract. Cyanobacterial blooms are common ecological problems that pose significant harm to humans, animals, and the health of lake ecosystems. To cope with this problem, we adopt a bio-dynamic model inspired by the invasion species and develop an integrated simulation-optimization model (Mixed Integer Programming) to effectively minimize the economic losses caused by cyanobacteria blooms. Based on the above, we also conduct computational experiments to validate the model. Test results have shown that the duration of treatment and budget have an impact on the damage, and timely algae removal is necessary to prevent further spread of cyanobacteria in the study area. This study represents an innovative interdisciplinary research achievement and can provide more accurate decision support to lake water quality managers in terms of algae removal site selection, frequency of operations, and operational pathways.

Keywords: Cyanobacteria blooms management, Mixed Integer Programming, interdisciplinary research

1 Introduction

Cyanobacterial blooms are common ecological problems resulting from eutrophication [1], and in the context of water bodies, they are considered as invasive species. Some cyanobacteria release microcystin toxins into the water [2,3], posing a threat to human health and biodiversity. Due to the urgent need to ensure water safety, cyanobacterial control has become one of the current hot topics in academia and the business sector.

Therefore, exploring the biological characteristics and growth dynamics of cyanobacteria is crucial to finding more effective methods for monitoring, predicting, and responding to bloom outbreaks. Scholars and practitioners also use mathematical models [4], deep learning [5], and remote sensing technology [6] to research cyanobacteria treatment.

Different from the existing literature, we describe the cyanobacteria management problem as an invasive species management problem [7-9]. Furthermore, in practical management, the resources available to managers (such as funding and labor) are typically limited. Thus, optimizing the allocation of these limited resources in space and

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time to minimize the economic and environmental damage caused by cyanobacteria can be formulated as a combinatorial optimization model for resource allocation. We present a novel approach to the management of cyanobacterial blooms by describing it as a combined problem of invasive species management and resource allocation optimization.

2 Model formulation

2.1 Problem description

This study divides the complex spatio-temporal mixed-integer optimization model into two key components. One is the simulation model, which aims to simulate the dispersal and growth processes of cyanobacteria in nature. The other is the optimization model, which aims to provide treatment strategies by analyzing the optimal treatment locations and paths to minimize economic losses and reduce costs. In this integrated model, there is an interactive coupling between the simulation model and the optimization model.

2.2 Mathematical model

2.2.1 Simulation model.

$$LD_{ijt} = \sum_{k=1}^{n} \sum_{(h,q)\in\Delta^{ij}} \omega_{hq} \alpha^{\varepsilon}_{(h,q)\to(i,j)} P^{k}_{hqt} L_k \qquad \forall i, j, t \tag{1}$$

$$LR_{ijt} = (1-\omega_{ij}) \sum_{k=1}^{n} P^{k}_{ijt} L_k \qquad \forall i, j, t \tag{2}$$

$$LB_{ijt} = LB_{ij0} (\zeta - \lambda)^{t} + \sum_{g=0}^{t} [(\zeta - \lambda)^{t-g} (LD_{ijg} + LR_{ijg})] \qquad \forall i, j, t \tag{3}$$

$$TP^{k}_{ij,t+1} = \lambda \rho LB_{ijt} \quad k = 1 \text{ and } \forall i, j, t \tag{4}$$

$$TP^{k}_{ij,t+1} = P^{k-1}_{ijt} (1-\varphi_{k-1}) \quad k = 2,3,\dots,n \text{ and } \forall i, j, t \tag{5}$$

$$P^{k}_{ijt} = \min\{TP^{k}_{ijt}, K_{ij}\} \quad k = n \text{ and } \forall i, j, t \tag{6}$$

$$P^{k}_{ijt} = \begin{cases} 0, K_{ij} - \sum_{b=k+1}^{K} P^{b}_{ijt} \le 0 \\ \min\{(K_{ij} - \sum_{b=k+1}^{n} P^{b}_{ijt}), TP^{k}_{ijt}\}, others \end{cases} \quad k = 1,2,\dots,n-1 \text{ and } \forall i, j, t \tag{7}$$

Eq (1) is the quantity of spores spreading from (h,q) to (i,j). However, a portion of the spores does not disperse and remains in the original cell, as shown by Eq (2). The spores that stay at the original cell and those that disperse from nearby cells form a spore bank, the quantity of which is shown by Eq (3). Eqs (4)-(5) represent the number of spores germinating into the first-stage cyanobacteria and continuously progressing to the stage k. Eqs(6)-(7) reflect the environmental carrying capacity in nature, no new cyanobacteria can be produced unless high-stage cyanobacteria die out to make room.

2.2.2 Optimization model.

The optimization model described in this section is a MIP that determines the optimal search and treatment strategy for the cyanobacteria provided by the simulation model. To distinguish the time variable t in the simulation model, let the time variable of the optimization model be denoted as t', representing the time steps used for ordering site visits. It is assumed that each time step will visit one site, and all visited sites will be searched, but the decision to perform treatment depends on the availability of budget. The decisions made at each time step involve: (1) which sites to search and visit, (2) whether to treat on the visited site.

$$\min \sum_{i=1}^{I} \sum_{j=1}^{J} RE_{ij} \cdot \sum_{k=1}^{n} AP_{ijk} \big/ K_{ij} \tag{8}$$

$$\sum_{j=1}^{J} (x_{1j1} + x_{Ij1}) + \sum_{i=2}^{I-1} (x_{i11} + x_{iJ1}) = 1 \tag{9}$$

$$\sum_{j=1}^{J} (x_{1jt'} + x_{Ijt'}) + \sum_{i=2}^{I-1} (x_{i1t'} + x_{iJt'}) \geq z_{t'} - z_{t'+1} \quad \forall t' \quad t' \neq 1 \tag{10}$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} x_{ijt'} = z_{t'} \quad \forall t' \tag{11}$$

$$\sum_{(h,q)\in\Delta^{ij}} x_{hq,t'+1} \geq x_{ijt'} + z_{t'+1} - 1 \quad \forall i,j,t' \quad t' \neq T' \tag{12}$$

$$z_{t'+1} - z_{t'} \leq 0 \qquad \forall t' \tag{13}$$

$$\sum_{t'=1}^{T} x_{ijt'} \leq 1 \qquad \forall i,j \tag{14}$$

$$\sum_{t'=1}^{T} x_{ijt'} \geq y_{ij} \qquad \forall i,j \tag{15}$$

$$AP_{ijk} = BP_{ijk}(1 - \theta_{ij} y_{ij}) \qquad \forall i,j,k \tag{16}$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} (C_{ij} y_{ij} + \sum_{t'=1}^{T'} H_{ij} x_{ijt'}) \leq \Upsilon \tag{17}$$

Eq (8) represents the objective function of the model, which aims to minimize the damage caused by cyanobacterial blooms. Eq(9) initiates the search and treatment process from one of the boundary locations, while Eq(10) requires the manager to exit from one of the boundary locations. Eq(11) ensures that the manager, can only search one location at a time. Eq(12) ensures that the next step can only visit and search neighboring sites. Eq(13) is used to ensure the continuity of the search path. Eq(14) ensures that each site can be visited only once. Eq(15) ensures that only searched sites can be treated. Eq(16) is used to calculate the cyanobacteria population after treatment. Eq(17) ensures that the cost of search and treatment is under the available budget.

3 Computational experiments

Table 1. Parameter setting

Model parameter	**Symbol**	**Value**	**Reference**
Number of spores produced per cyanobacteria	L_k	[40,80,20]	Estimated
Loss rate from stage $k-1$ to stage k	φ_k	[0.06,0.17]	[10]
Survival rate of spores	ζ	85%	Estimated
Germination rate of spores	λ	16.8%	Estimated
Probability of becoming first-stage cyanobacte-	ρ	80%	Estimated
Maximum carrying capacity per cell	K_{ij}	6,000,000	Estimated
Effectiveness rate of treatment for cell (i,j)	θ_{ij}	90%	[11]
Treatment cost	C_{ij}	500	Estimated
Search cost	H_{ij}	15	Estimated
Expected revenue in cell (i,j) at time t	RE_{ij}	3,000	Estimated

Using the parameter values in Table 1, we simulate the population growth of cyanobacteria over 60 days (every time step is 10days). As shown in Figure 1., neighboring sites are affected initially, and then the spread grows radially outward over the time.

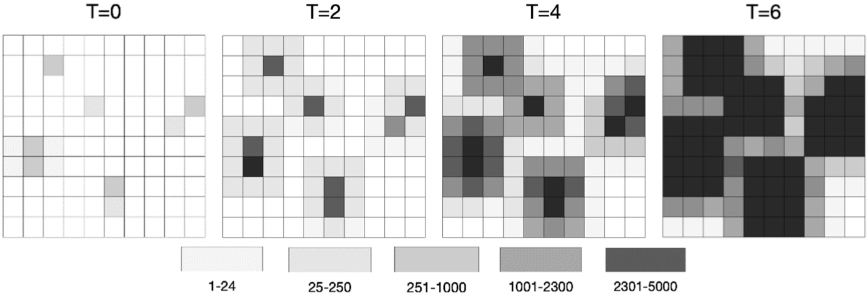


Fig. 1. Simulation model output for cyanobacteria over 60 days

We also study the relationship between budget, time, and damage. The results are presented in Table 2, where the columns represent the budget (RMB), search and treatment time(days), expected damage (RMB), gap (%), and solving time (seconds), respectively.

Table 2. Total damage based on different budget and search time

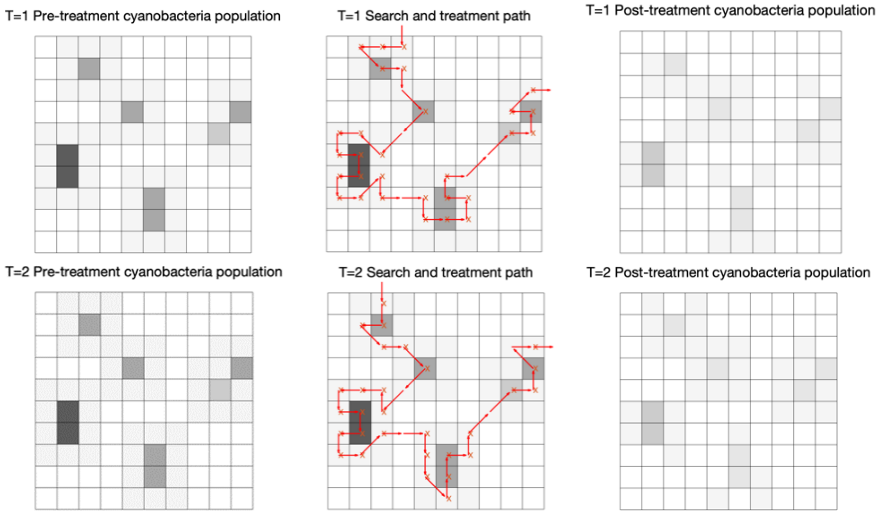
Budget	*Search and treatment time*	*Damage*	*Gap*	*Solving time*
10,000	20	0.8335	0.69	110.44
10,000	22	0.7966	0.07	129.31
10,000	24	0.7934	0.03	139.34
10,000	26	0.7933	0.01	427.19
10,000	28	0.7933	0.02	947.18
15,000	28	0.7777	0.14	1748.73

15,000	32	0.7684	0.13	1800
15,000	36	0.7676	0.03	1800
15,000	40	0.7676	0.03	1800
15,000	44	0.7679	0.06	872.89
20,000	42	0.7495	0.02	670.02
20,000	44	0.7495	0.02	1438.25
20,000	46	0.7495	0.02	1489.58
20,000	48	0.7496	0.03	1345.92
20,000	50	0.7498	0.08	1207.12

1. Regardless of whether the budget is 10,000, 15,000, or 20,000, there are consistent laws in the damage, gap, and solving time. As the search and treatment time increases, the damage caused by cyanobacterial blooms decreases because more cells may be searched. Thus, it will lead to a reduction in the gap. However, as time continues to increase, the damage no longer decreases. This is because the budget is limited, and the increasing search cost will reduce the treatment cost, resulting in fewer cells be treated and ultimately leading to an increase in the cyanobacteria population.

2. As the budget increases, both the damage and gap decrease, but the solving time increases. When the budget increases from 10,000 to 15,000, the damage decreases. This is because more cells can be treated under a sufficient budget. Simultaneously, there are more possible paths to choose from, and the software needs to select the shortest path, leading to an increase in solving time. The same laws apply when the budget increases from 15,000 to 20,000.

Then, we reconstruct the search and treatment path at each time step and show the changes in cyanobacteria population before and after treatment in Figure 2.



T=1 Pre-treatment cyanobacteria population

T=1 Search and treatment path

T=1 Post-treatment cyanobacteria population

T=2 Pre-treatment cyanobacteria population

T=2 Search and treatment path

T=2 Post-treatment cyanobacteria population

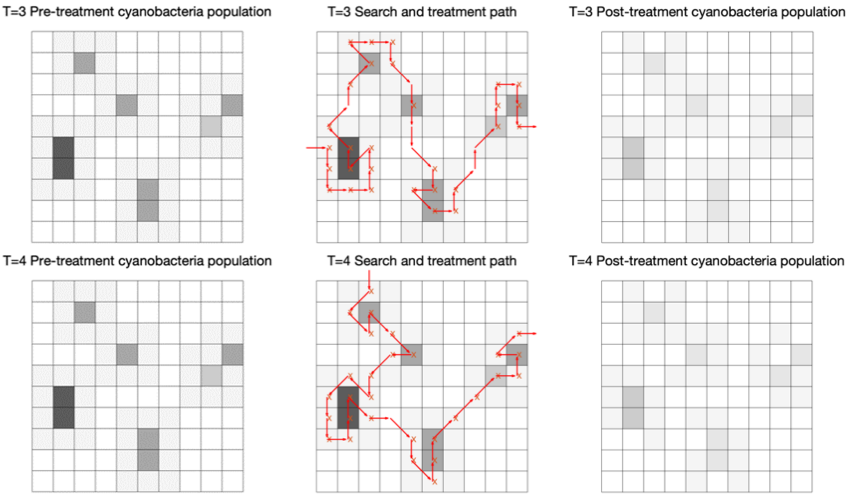


Fig. 2. The search and treatment path, cyanobacteria population before and after treatment

From the Figure 2, it can be observed that the search and treatment paths revolve around cells with high invasion abundance. Although the entry and exit cells may differ, the paths exhibit a high level of similarity. As time progresses, the paths gradually shorten. Timely treatment can prevent the further spread of cyanobacteria, thereby mitigating greater damage.

4 Conclusions

(1) The duration of treatment and budget have an impact on the damage. Longer treatment time and sufficient treatment budget provide more opportunities to control the spread of cyanobacteria, reducing their impact on ecosystems and human health.

(2) Timely and frequent treatment can effectively suppress the outward expansion of cyanobacteria and prevent greater economic losses.

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