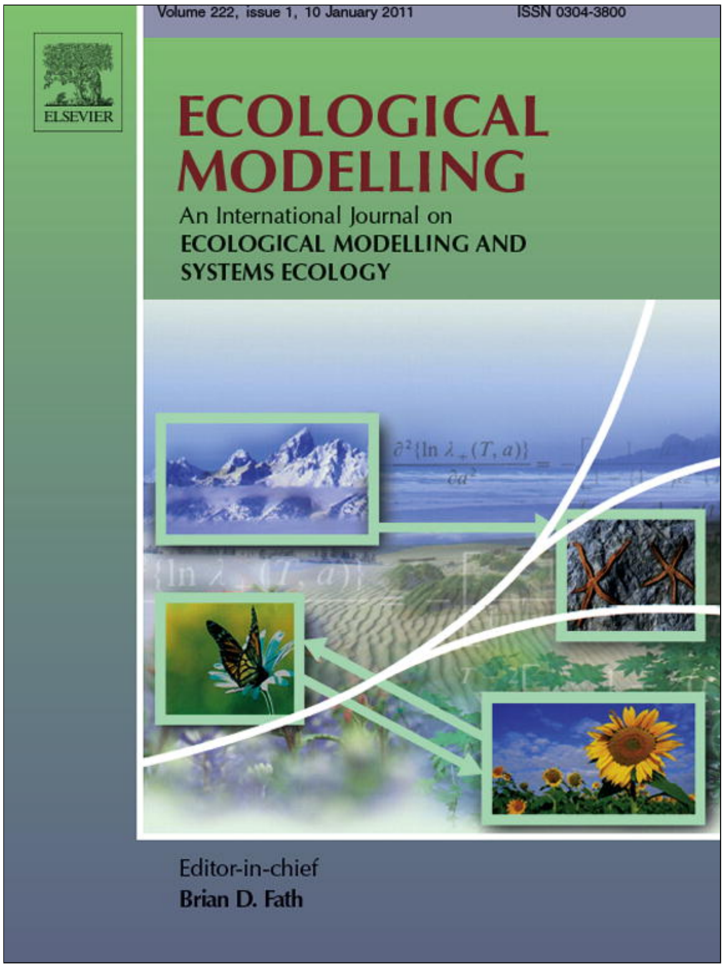
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A mathematical model of algal blooms based on the characteristics of complex networks theory

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ABSTRACT

To predict the outbreak time of algal blooms and its duration in an actual body of water, this paper developed a directed complex networks (CNs) model of algal blooms. This new model was based on the characteristics of CNs theory and the primary factors that influenced algal blooms. By calculating the shortest path and proposing a key degree node model, the role of each influencing factor during algal blooms was evaluated. Based on years of on-site monitoring data (collected from 1992 to 2000) concerning the Han River, a statistical characteristic function G that reflected the relationship between the statistical characteristics of dominant algae blooming and the degree of algal blooms pollution was proposed. The results indicate that the proposed function G is capable of effectively and semi-quantitatively characterizing the outbreak time and the duration of algal blooms. If the value of G in a body of water is less than 32.6, the body of water will outbreak an algal bloom. An increasingly smaller of G value indicates a greater degree of algal blooms pollution and longer bloom duration.

1. Introduction

A persistent view, called the 'global spreading hypothesis', maintains that the frequency, magnitude and geographical extent of harmful algal blooms have increased in recent decades (Jordan and Wyatt, 2006). The apparent increasing worldwide occurrence and impact of harmful algal blooms (HABs) events have commonly been directly or indirectly attributed to an increased incidence of eutrophication (Hallegraeff, 1993; Anderson et al., 2002; Glibert et al., 2005a,b; Glibert and Burkholder, 2006; GEOHAB, 2006). Such blooms invariably induced serious public health risks because most blooming algae produced toxins, including hepatotoxins and neurotoxins, and malodorous compounds, such as geosmin and 2-methylisoborneol (MIB) (De Figueiredo et al., 2004). On the basis of water quality monitoring data and relevant water environmental material data that have been gathered over many years, it is possible to investigate the dynamic mechanism of algal blooms thoroughly and clearly. Vollenweider (1975) explored the elementary mass balance and export models that were relevant to phosphorus- and nitrogen-induced eutrophication. Additionally, Kuo et al. (2006) developed a combined neural network and genetic algorithm (GA) for water quality management. Large amount of investigations of the effects of upwelling on harmful algal blooms (HABs) off the west coast of Florida (Lanerolle et al., 2006) was developed into a useful tool for predicting the onset of HABs and examining their dynamics due to upwelling. And the Spatially Referenced Regressions on Watersheds (SPARROW) model was extensively used in the USA to estimate nutrient loads to receiving waters, such as in the Gulf of Mexico (Robertson et al., 2009; Hoos and McMahon, 2009). In the SPARROW model, statistical relationships were employed to relate water quality monitoring data to upstream sources and watershed characteristics that affected the fate and transport of nutrients (Glibert et al., 2010).

A water body during algal blooms is an open system of nonlinear complex dynamics with characteristics of multi-factor interaction and multi-dimensional cooperation (Zhan et al., 2009). It is impossible to describe and elucidate the inner evolutions of algal blooms completely quantitatively by using contemporary research methods and theories. For example, although fluid dynamics and neural network algorithms could capture the trends of algal dynamics, the results usually exhibited solution divergence, and they fell into local optima (Lee et al., 2003; Huisman and Sommeijer, 2002). Biochemical theories and experiments could forecast future algal composition and abundance accurately, but researchers were unable to reasonably explain or predict the time that an algal

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blooms will explode or subside, including the pollution distribution and scale therein (Salacinska et al., 2010).

Watts and Strogatz (WS) (1998) proposed a model that interpolated between a regular ring lattice and a random graph. Since then, the study of complex networks (CNs) gradually coalesced into a complete independent discipline called the "new science of networks" (Watts, 2004). The new theory of CNs has permeated into the life sciences, engineering sciences, social sciences and other different fields (Elgazzar, 2003; Tatem and Hay, 2007; Galvao and Miranda, 2008). With further investigation, the main properties of CNs have attracted significant attention in recent years. For example, Allesina and Bodini (2004) used the topological structures theory of CNs to investigate the problem of secondary extinction in food webs. Chatlines in the framework of social networks have been studied using the dynamics of CNs (Guazzini et al., 2010). In addition, both the robustness and vulnerability of CNs were discussed in the field of power grids (e.g., Sole et al., 2008; Mishkovski et al., 2011).

According to graph theory and statistical patterns, CNs can be used to process and resolve numerous problems that occur in complex systems based on the following points such as overall behavior, synchronic effects, statistical characteristics, transitivity and small-world effect (Watts, 2004; Allesina and Bodini, 2004; Guazzini et al., 2010). Unfortunately, the study of algal blooms using CNs has received sparse attention, and there is little available data. A paper that was relevant to this research was published by Zhan (Zhan et al., 2009), who is a member of our team, in Acta Scientiae Circumstantiae, China. Therein, the synchronization of CNs theory used to judge whether algal blooms outbreaks can be used to characterize the state of pollution in the Three Gorges Reservoir Area of the Yangtze River.

In this study, an algal blooms statistical characteristics function G is formulated by constructing a directed CNs model of algal blooms and a series of statistical characteristics calculations. This function can be used to predict the time and duration of the outbreak in an actual body of water.

2. Materials and methods

2.1. Directed CNs of an algal blooms

Supposing that an actual body of water can be abstracted as a complex networks (CNs) consisting of a set of nodes, we take potential factor that influenced algal blooms as a node in the CNs, which, together, constitute a set of points V ($V = \{v_1, v_2, \ldots, v_n\}$). The edges that represent the interactions among the nodes are abstracted as a set of edges E ($E = \{e_1, e_2, \ldots, e_m\}$). Then, the graph $G = (V, E)$, which is composed of V and E, can reflect the actual state of the algal blooms waters, and we denote the number of nodes and the number of edges as $n = |V|$ and $m = |E|$, respectively (Newman, 2003; Wang et al., 2006). Each edge in E has a corresponding pair of nodes. A directed complex networks, as defined by Newman (2003), is a complex network that composed of directed edges.

Many factors regulate changes in water ecosystems (Kagalou et al., 2008). Generally, the algal blooms process is considered to be a response to nutrient loading, such as total nitrogen (TN) and total phosphorus (TP), and a response to hydrological factors, such as water temperature (T), flow velocity (v), pH, dissolved oxygen (DO), light intensity (I), algae density (ρ), and species of algae (N) (Glibert and Bronk, 1994; Glibert et al., 2005a,b; Kemp et al., 2005; Liu et al., 2005a,b, 2006, 2007; Glibert and Burkholder, 2006; Hood et al., 2006; Heisler et al., 2008; Liu and Zhang, 2008; Zhan et al., 2009; Long et al., 2011). As the size of the diversity of an investigated system increases, more information will be available that can be used to understand the interactions of the influencing factors.

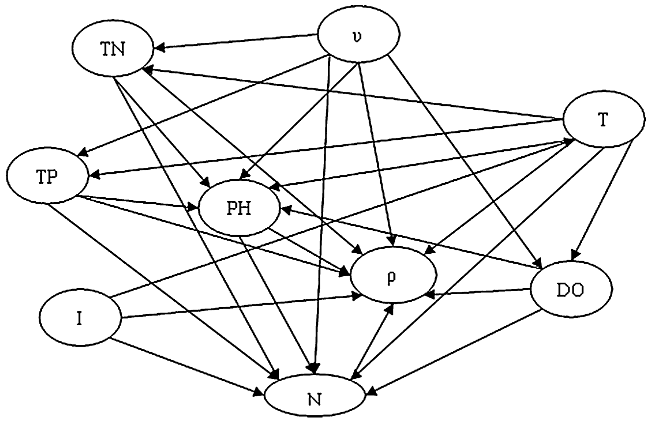

Fig. 1. The directed CNs model of algal blooms with $n = 9$ nodes and $m = 27$ edges. TN, total nitrogen; TP, total phosphorus; T, water temperature; v, flow velocity; DO, dissolved oxygen; I, light intensity; N, species of algae; ρ, algae density.

Thus, it is important to find out the potentially influential factors and build a directed CNs model in order to evaluate algal blooms processes, including algal blooms outbreak time, the degree of algal blooms pollution, and algal blooms duration and scale. To build a directed CNs model of algal blooms in this study, we took nine influencing factors into account, and each influencing factor was abstracted as a node in the model. The edge between two nodes was described as the interaction of two influencing factors. Fig. 1 depicts the directed CNs model of algal blooms.

According to the direct effects and appearances of the influencing factors on algal blooms processes, we classify the nine factors into three levels, as follows:

(1) TN, TP, T, v and I are established as the first influencing factor level (basic), for the five factors are most easily affected by outside influences.
(2) pH, DO, and N are affected by both external influences and the functions of nutrients in the water; hence, these factors are established as second level factors.
(3) Because the visual appearance of an algal blooms is directly a function of the rapid proliferation and growth of algae, ρ is established as a third level, which represents the terminal of the directed CNs.

2.1.1. The characteristics of CNs

In recent years, numerous concepts and methods have been proposed and used to depict the characteristics of CNs. These studies primarily focused on the average path length (L), clustering coefficient (C), and degree (k_i) in CNs (Wang et al., 2006). In addition, to better reflect the circulation of data between any two nodes when calculating the shortest path, this paper took the betweenness (B_i) into account.

2.1.2. The average path length (L)

The average path length (L) is the average geodesic distance between any two nodes, and it is also the shortest distance that links two nodes at one time (Wang et al., 2006). The essence of L involves the probability statistics that interact in an entire network. The calculation of L between node v_i and node v_j is:

$$L = \frac{1}{(1/2)N(N-1)} \sum_{i \geq j} d_{ij} \qquad (1)$$

where N is the number of nodes, and d_{ij} is the geodesic distance from node v_i to node v_j.

Table 1
The correlation coefficients of influencing factors during algal blooms. The data is processed with the software of SPSS16.0.

No.	Influencing factors	TN	TP	T	v	pH	DO	I	N	ρ
1	TN	1	0	0.295	0.12	0.036	0	0	0.1962	0.249
2	TP		1	0.131	0.19	0.506	0	0	0.0573	0.863
3	T			1	0	0.218	0.275	1	0.0083	0.187
4	v				1	0.15	0.51	0	0.0064	0.771
5	pH					1	0.828	0	0.0079	0.640
6	DO						1	0	0.0170	0.732
7	I							1	0.0413	0.164
8	N								1	0.992
9	ρ									1

2.1.3. Degree (k_i)

The degree k_i of a node v_i is the number of edges that are incident with others. There is the idea of out-degree and in-degree in directed CNs, wherein the out-degree of a node v_i is the number of edges from node v_i to others. The in-degree of v_i is the number of edges from other nodes to v_i. The greater the degree of a node, the more important the role it plays in the entire network (Wang et al., 2006).

2.1.4. Clustering coefficient (C_i)

For each node, the clustering coefficient C_i is defined as the ratio of the number of edges (E_i) among the nodes within its neighborhood divided by the total number of edges ($k_i(k_i-1)/2$) that could possibly exist among them (Newman, 2003). It can be quantified by defining a clustering coefficient C_i as follows:

$$C_i = \frac{2E_i}{k_i(\,k_i-1)} \qquad (2)$$

where k_i is the number of edges of a node that connect to other nodes. Then, the clustering coefficient C within the entire network is the average of C_i over all of the nodes. By definition, we know that $0 \le C_i \le 1$ and $0 \le C \le 1$.

2.1.5. Betweenness (B_i)

Betweenness (B_i) is the number of times that node v_i is passed when calculating the shortest path in CNs (Freeman, 1977, 1979). In general, a sparse CNs has a low betweenness, whereas a dense CNs has a high betweenness.

According to the characteristics of CNs, the interaction of any two factors can be expressed by the average path length. The clustering coefficient is mapped by the degree of interaction among factors. The contribution rate of each node is mapped to a key degree, and the betweenness can be understood as the number of times that node v_i is passed when calculating the shortest path in a CNs. Therefore, the complex interactions and degrees in nonlinear factor influences can be completely delineated.

2.2. Numerical computation

2.2.1. Correlation analysis and edge distances

Correlation (relevance) analysis is a common statistical method to study the relationship between two or more variables, and correlation coefficient is a value of measuring the closeness of them (Mizzaro, 1997). The correlation coefficients of the influencing factors are calculated on the basis of actual winter and spring algal blooms values in the Daning River, which is a tributary of the Three Gorges Reservoir Area (Cao et al., 2009). Table 1 depicts the calculating results of correlation coefficients.

In Table 1, the correlation coefficients between ρ and the first influencing lever factors (TN, TP, T, v, and I) are 0.249, 0.863, 0.187, 0.771, and 0.164, respectively. These data means that the effects of nutrients on ρ is larger than the geography factors (T, v, and I), and the influence of TP to ρ outweigh TN's. The correlation coefficient between N and ρ is 0.992, which is the greatest value in the second level factors, and that means that they are closely related.

In this study, each influencing factor is regarded as a node in a CNs, and set r_{ij} is the correlation coefficient between nodes v_i and B_j. We can obtain the edge distances W_{ij} ($i, j = 1, 2, \ldots, 9$) between each two nodes via the normalization method [Xiao et al., 2005, Eq. (5.3.2)]. And the calculation results of the edge distances were shown in Table 2.

$$W_{ij} = \frac{\sum_{i,j=1}^{n} r_{ij}}{r_{ij}} \quad \text{and} \quad i, j = 1, 2, \ldots, n; \quad n = 9. \qquad (3)$$

The results of Table 2 demonstrate that these nodes between TN and T, T and DO, v and DO, TN and N, and TP and v have high probabilities of being passed through when calculating the shortest paths, because the edge distances between them are obviously smaller than others. In other words, these interactions contribute greatly to the algal density. The values of edges that are marked as either "0" or "∞" in Table 2 indicate that the directed path between a pair of nodes does not exist in the CNs.

2.2.2. Numerical computation of the characteristics

In this paper, the Floyd algorithm was used to calculate the shortest distances and specific paths between each pair of nodes

Table 2
The edge distances of the directed CNs model of algal blooms.

No.	Influencing factors	TN	TP	T	v	pH	DO	I	N	ρ
1	TN	0	∞	1.4	3.5	48.3	∞	∞	1.7	20
2	TP	∞	0	2.5	1.7	3.4	∞	∞	5.9	5.3
3	T	1.4	2.5	0	∞	8.0	1.4	1	33.3	25
4	v	3.5	1.7	∞	0	11.6	1.5	∞	50	5.9
5	pH	48.3	3.4	8.0	11.6	0	2.1	∞	50	7.1
6	DO	∞	∞	1.4	1.5	2.1	0	∞	20	6.3
7	I	∞	∞	1	∞	∞	∞	0	8.3	25
8	N	1.7	5.9	33.3	50	50	20	8.3	0	4.8
9	ρ	20	5.3	25	5.9	7.1	6.3	25	4.8	0

Table 3
The shortest distances of the directed CNs model of algal blooms.

No.	Influencing factors	TN	TP	*T*	*v*	pH	DO	*I*	*N*	*ρ*
1	TN	0	–	–	–	48.3	–	–	1.7	6.5
2	TP	–	0	–	–	3.4	–	–	5.9	5.3
3	*T*	1.4	2.5	0	–	5.0	2.9	–	3.1	7.8
4	*v*	3.5	1.7	–	0	3.6	1.5	–	5.2	5.9
5	pH	–	–	–	–	0	–	–	50	7.1
6	DO	–	–	–	–	2.1	0	–	20	6.3
7	*I*	2.4	3.5	1.0	–	6.0	3.9	0	4.1	8.8
8	*N*	–	–	–	–	–	–	–	0	4.8
9	*ρ*	–	–	–	–	–	–	–	–	0

within the CNs (Tsai et al., 2004). The calculations are given in Tables 3 and 4.

In Table 4, we can depict the nodes that can directly reach node v_9, which include TP, v and the second level factors (pH, DO and N). This table indicates that these nodes cannot affect other factors; however, these nodes can directly impact ρ and change it, ultimately resulting in algal blooms. Furthermore, according to Table 4, it can be observed that TN could indirectly affect ρ by influencing the species of the dominant algae (N). In addition, the water temperature (T) influences the algal blooms through TP, for T can change the form of phosphorus existing in water body (Liu et al., 2006; Liu and Zhang, 2008). Light intensity (I) indirectly affects algal blooms through the nodes of T and TP. In summary, we can obtain the shortest path from node I (v_7) to node ρ (v_9): $I \rightarrow T \rightarrow \mathrm{TP} \rightarrow \rho$. The detailed paths that each node arrives at on the end [the algae density (ρ)] are summarized in Fig. 2 according to the results of Tables 3 and 4.

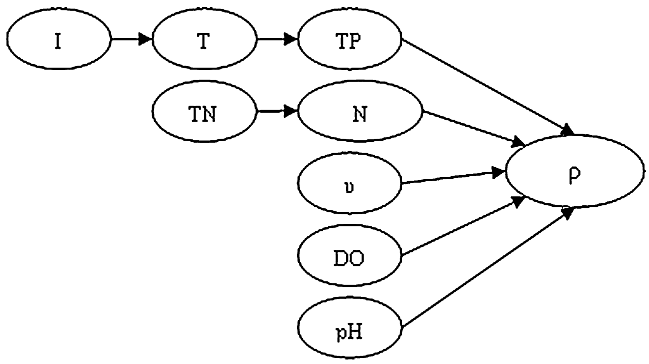

Fig. 2. The shortest paths of the influencing factors of algal blooms.

2.3. Key degree node model

To better depict the role of each node in the modeled algal blooms, we propose another parameter: the key degree node model σ_i (Wang et al., 2006), as shown in Eq. (4):

$$\sigma_i = \frac{\lambda_i^+ \times \lambda_i^-}{d_{\min}} \times B_i \qquad (4)$$

where λ_i^+ and λ_i^- represent the in-degree and out-degree of node v_i, respectively. The parameter $d_{\min}$ represents the shortest distance from node v_i to node v_9, and B_i represents the betweenness of node v_i. In the paper, we set the in-degrees of v and I as 1. Because the parameter σ_i takes the shortest distance, the betweenness and directed characteristics of node v_i into account, it is able to represent the role of node v_i in CNs. Notably, the higher the value of σ_i, the more important role node v_i plays in the entire algal blooms CNs.

Table 4
The shortest paths of the directed CNs model of algal blooms. These figures in this table represent different nodes/factors: (1) TN (total nitrogen), (2) TP (total phosphorus), (3) *T* (water temperature), (4) *v* (flow velocity), (5) pH, (6) DO (dissolved oxygen), (7) *I* (light intensity), (8) *N* (species of algae), and (9) *ρ* (algae density).

No.	Influencing factors	TN	TP	*T*	*v*	pH	DO	*I*	*N*	*ρ*
1	TN	1	–	–	–	5	–	–	8	8
2	TP	–	2	–	–	5	–	–	8	9
3	*T*	1	2	3	–	6	6	–	1	2
4	*v*	1	2	–	4	6	6	–	1	9
5	pH	–	–	–	–	5	–	–	8	9
6	DO	–	–	–	–	5	6	–	8	9
7	*I*	3	3	3	–	3	3	7	3	3
8	*N*	–	–	–	–	–	–	–	8	9
9	*ρ*	–	–	–	–	–	–	–	–	9

Table 5
Parameters of the directed CNs model of algal blooms.

Node	Clustering coefficient (C_i)	Node degree		Betweenness (B_i)	Key degree model (σ_i)
		In-degree (λ_i^+)	Out-degree (λ_i^-)		
TN	0.1389	2	3	5	4.62
TP	0.1389	2	3	4	4.53
T	0.1944	1	6	8	6.15
v	0.1667	1	6	1	1.02
pH	0.1944	5	2	4	5.63
DO	0.1389	2	3	5	4.76
I	0.0833	1	3	1	0.34
N	0.2222	7	1	6	8.75
Clustering coefficient of the whole CNs			0.1667		
Average path length			8.16		

Table 6
Local monitoring data of Feb. and Mar. in the Han River from 1992 to 2000. The Hanjiang River is 1570 km long, covers an area of 159,000 km^2. It is the second largest branch of the Yangtze River, China.

Year	TN ($mg\,L^{-1}$)	TP ($mg\,L^{-1}$)	T (°C)	v ($m\,s^{-1}$)
1992	1.216	0.0807	11.0	0.213
1993	1.329	0.0882	7.6	0.583
1994	0.973	0.0949	7.8	0.410
1995	1.085	0.0983	7.2	0.319
1996	1.246	0.0737	6.9	0.396
1997	1.336	0.0994	6.8	0.479
1998	1.653	0.1962	11.5	0.130
1999	1.494	0.1589	7.2	0.414
2000	1.354	0.1318	11.5	0.168

Table 7
Computing values under different hydrologic conditions and relative functions in Han River.

Year	G	Relative duration	The degree of algal blooms pollution
1993–1997, 1999	40.38–43.83	None	Not occurred, although sometimes have a higher degree eutrophication
1992	32.6	Short	Occurred, but quickly disappeared
2000	31.24	Long	Occurred, had a certain intensity
1998	30.71	Longer	Occurred, and the intensity is larger

Table 5 illustrates the parameters σ_i of the directed CNs model of algal blooms. The degrees of the influencing factors on algal blooms processes (see Table 5) can be ranked as N (8.75) > T (6.15) > pH (5.63) > DO (4.76) > TN (4.62) > TP (4.53) > v (1.02) > I (0.34).

3. Results and discussion

3.1. Building the algal blooms statistical characteristics function G

Although the parameters c_i, k_i, B_i and σ_i can describe many characteristics of the entire algal blooms CNs, they fail to assess the situation and degree of algal blooms. Based on an overall consideration of various factors (a clustering coefficient, the key degree node, the shortest distance), we build a statistical function of the algal blooms directed CNs, as shown in Eq. (5):

$$G = \frac{\sigma'_1 d_1 + \sigma'_2 d_2 + \sigma'_3 d_3 + \sigma'_4 d_4 + \sigma_5 d_5 + \sigma_6 d_6 + \sigma_7 d_7 + \sigma_8 d_8}{8} \quad (5)$$

where G is the statistical function of the directed CNs model, d_i denotes the shortest distance between node v_i and node v_9 ($d_{\min}$) and σ_i represents the key degree model of a node. In this study, we modified four parameters, TN, TP, T and v, for their contents change greater than others' in a body of water in a year. The modified equations are:

$$\sigma'_{TN} = \frac{c_{oTN}}{c_{TN}} \sigma_{TN} \quad (6)$$

$$\sigma'_{TP} = \frac{c_{oTP}}{c_{TP}} \sigma_{TP} \quad (7)$$

$$\sigma'_{T} = \frac{T_{oi}}{T_i} \sigma_{T} \quad (8)$$

$$\sigma'_{v} = \frac{V_i}{v_{opt}} \sigma_{v} \quad (9)$$

where c_i denotes the actual concentrations of the primary influencing factors that affect v_i, whereas T_i is the water temperature and V_i is the water flow velocity. Considering eutrophication from a single nutrient, it is generally believed that algal bloom is possible, when the contents of nitrogen (TN) and phosphorus (TP) exceed a certain critical concentration limit (the TP and TN concentrations, respectively, are 0.02 $mg\,L^{-1}$ and 0.2 $mg\,L^{-1}$), an algal blooming event is possible (Zhan et al., 2009). Correspondingly, the value of c_{oTN} is 0.2 $mg\,L^{-1}$ and c_{oTP} is 0.2 $mg\,L^{-1}$. Because v_{opt} = 0.1 $m\,s^{-1}$ is the optimal velocity of algal growth in a calm flowing river (Zhan et al., 2009), this study establishes v_{oi} as 0.1 $m\,s^{-1}$. When nutrient levels and other conditions are suitable, a water temperature of 28 ± 1 °C could promote algal blooms growth (Huang et al., 2009; Long et al., 2011) hence, we selected 28 °C as the value of T_{oi}.

3.2. Rating the algal blooms statistical function G

We processed recent monitoring data (shown in Table 6) (Zhan et al., 2009) of the Han River, which is the second largest branch of the Yangtze River, China, using Eq. (5), and the results are depicted in Table 7.

We carried out a semi-quantitative classification of the G function using the aforementioned monitoring data and relevant Three Gorges Reservoir tributary waters information. The results are as follows:

$$G = \begin{cases} \le 30.7 & \text{large-scale algal blooms} \\ (30.7,\ 31.3) & \text{serious algal blooms} \\ (31.3,\ 32.6) & \text{obvious algal blooms} \\ (32.6,\ 40.0) & \text{slight algal blooms} \\ \ge 40.0 & \text{none} \end{cases}$$

Table 8
G values under different hydrologic conditions and relative parameters in different water areas.

Monitoring sites	Year	TN ($mg\,L^{-1}$)	TP ($mg\,L^{-1}$)	T (°C)	v ($m\,s^{-1}$)	G	Relative duration	The degree of algal blooms pollution
Xiantao section of Hang River	March, 2000	0.14	2.04	14	0.69	36.94	Short	Slight
Xiakou section of Xiangxi River	May and June, 2005	2.96	0.52	21	0.009	22.80	Long	Occurred and the intensity is larger
Gaolan section of Xiangxi River	June and July, 2008	2.96	0.09	26.5	0.056	22.05	Long	Occurred and the intensity is larger

3.3. The verification of function G

The data that were obtained from water quality monitoring of the Xiantao section of the Hang River (Liu et al., 2005a,b), the Xiakou section of the Xiangxi River (Wang et al., 2007), and the Gaolan section of the Xiangxi River (Yang et al., 2010) were used to verify *G*. Table 8 summaries the calculated *G* values.

The calculated *G* value (see Table 8) of the Xiantao section in March 2000 falls within the range of 32.6–40.0, which indicates that this section had a slight algal blooms during that time. According to water quality reports at that time, floating cyanobacteria and large filamentous algae were observed in the river. According to water analysis of the Xiakou section, *G* is equal to 22.80, indicating that the river experienced a large, strong and lengthy algal blooms in May and June of 2005, which matches the actual river condition at that time. A serious algal blooms happened in the Gaolan section in June and July of 2008, and the resultant *G* was calculated to be 22.05. A comparison between the simulated and measured data indicates that our forecasting results agree well with the actual water quality monitoring data.

4. Conclusions

From the correlation (relevance) analysis, the effects of nutrients (TP, TN) on ρ is larger than the geography factors (T, v, I), which means that the effects of nutrients on ρ is larger than the geography factors. The influence of TP to ρ outweigh TN's that explain why TP play a key role in algal blooms. The correlation coefficient between N and ρ is the greatest in the three levels. That means species of algae (N) are closely related to algae density (ρ).

We can come to the conclusion that the nodes of TP, v and the second level factors (pH, DO and N) could directly reach node v_9 (ρ). And others have to indirectly influence algal blooms by directly influencing other factors. TN could indirectly affect ρ by influencing the species of the dominant algae (N). In addition, the water temperature (T) influences the algal blooms through TP, light intensity (I) indirectly affects algal blooms through the nodes of T and TP.

This paper presented a new computational model to study algal blooms processes by using the characteristics of CNs theory and the interactions of the primary influencing factors contained there. In addition, we built a key degree node model in order to describe the role of each influencing factor in algal blooms. Using water quality monitoring data of the Han River (1992–2000), we established the statistical characteristics function G as an assessment criterion for evaluating algal blooms processes. Here, based on a long time and continuous monitoring of the water body, the proposed function G can predict the algal blooms outbreak time, degree of algal blooms pollution, and algal blooms duration and scale. The results indicate that G can effectively represent the state of algal blooms in a semi-quantitative way.

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