A simple tool for the early prediction of the cyanobacteria Nodularia spumigena bloom biomass in the Gulf of Finland*

OCEANOLOGIA, 48 (S), 2006. pp. 213–229.

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KEYWORDS Harmful algal blooms Nodularia spumigena Fuzzy logic model Gulf of Finland

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Received 12 December 2005, revised 12 May 2006, accepted 18 May 2006.

Abstract

A fuzzy logic model for predicting the maximum biomass of the toxic cyanobacteria *Nodularia spumigena* bloom in the Gulf of Finland is suggested. The model bloom biomass depends on the phosphate conditions up to 15 June, including the excess phosphate left over after the spring bloom and on the phosphate inputs parameterised by wind mixing and upwelling from 1 May to 15 June. The surface layer temperature, set to vary from 14 to 23° C, is regarded as a bloom regulating parameter. The model simulations showed that the predicted *N. spumigena* biomasses differ markedly from year to year and clearly depend on phosphate conditions up to 15 June.

 $^{^{\}ast}$ This study was partly supported by EC project HABES (contract No EVK2-CT-2000-00092).

The complete text of the paper is available at http://www.iopan.gda.pl/oceanologia/

1. Introduction

Late-summer cyanobacterial blooms, including the potentially toxic Nodularia spumigena Mertens and Aphanizomenon flos-aquae (L.) Ralfs are common in the eutrophic Baltic Sea (e.g. Kahru et al. 1994, Finni et al. 2001) and are as old as the present brackish water phase of the sea (Bianchi et al. 2000). Annual cumulative satellite maps of the cyanobacterium N. spumigena surface accumulations show that in the early 1990s the blooms occurred in the Northern Baltic Proper but never extended into the Central and Eastern Gulf of Finland (Kahru et al. 1994). The recurrence of massive blooms in the Gulf of Finland since 1995 is most likely related to a remarkable increase in the winter dissolved inorganic phosphorus (DIP) concentration, despite the decrease in the external phosphorus and nitrogen load by about 30% in the 1990s (Pitkänen et al. 2001). The increase in DIP concentration caused by the internal load over the whole Gulf area is explained by poor oxygen conditions at the sediment-water interface, which increases the benthic release of phosphorus (Heiskanen et al. 2000, Pitkänen et al. 2001). Field data from 1992–2002 showed a good correlation between the annual maximum biomass of N. spumigena in warm summers and the excess phosphate left over after the spring bloom (Laanemets et al. 2006); the excess phosphate is therefore considered to be a source of phosphate in the model. Owing to the peculiarities of the vertical distribution of phosphate and nitrate, such as the phosphacline being located in the upper part of the thermocline and the nitracline about 5 m deeper (Laanemets et al. 2004), the pre-bloom wind-induced mixing and upwellings transport an additional amount of phosphate into the surface layer. Besides the phosphorus conditions, the surface layer temperature is an important aspect for the initiation of the N. spumigena bloom by setting the threshold at about 16°C (Lehtimäki et al. 1997).

The intensity and spatial extension of the cyanobacterial bloom in the Gulf of Finland had been forecast for several years using a deterministic ecosystem model (Kiirikki et al. 2001). This was done in spring for three different weather scenarios, with the winter nutrient concentrations in the surface layer being taken into account. Although almost real-time information on the cyanobacterial situation in the Central Gulf of Finland is available from the Alg@line project (e.g. Rantajärvi & Leppänen 1995) as well as from satellite remote sensing data, a simple tool for the early prediction of the expected bloom biomass is still missing.

The aim of this work is to suggest a simple fuzzy-logic-based model for the early prediction of the expected N. spumigena bloom biomass in summer. In order to simplify the model setup the number of model input parameters (predictors) is minimised: only the winter dissolved inorganic nitrogen (DIN), DIP, and the spring wind data are considered. These data are publicly accessible for almost all regions of the Baltic Sea, which makes this approach more attractive. The model considers the bloom-limiting amount of phosphate left over by the 15 June and calculates the expected biomass as a function of the surface layer water temperature.

The advantage of using fuzzy logic, introduced by Zadeh (1965), is the possibility of applying expert knowledge even if the required exact relationships have not been fully established. In the context of this research, the application of a fuzzy-logic model also enables N. spumigena to be singled out from other blooming cyanobacterial species for further study.

2. Material and methods

2.1. The data

In this study the wind, surface layer temperature, N. spumigena biomass and winter nutrient data measured in 1997–2004 were used. Winter (January) nutrient data (DIN and DIP), sampled in the upper layer at monitoring station F3, were used for calculating the excess phosphorus after the spring bloom (Fig. 1). The data were collected within the framework of the HELCOM monitoring programme COMBINE. Wind data (from May to July) measured at the Kalbådagrund weather station (Finnish Meteorological Institute) at 3-hour intervals were used for parameterising the phosphate input from the upper part of the thermocline by turbulent mixing and upwelling. Turbulent mixing was considered a factor restricting N. spumigena growth. The N. spumigena biomass and the surface layer temperature data, collected unattended on passenger ferries plying between Tallinn and Helsinki (the Alg@line project), were used for calibrating and validating the model (Fig. 1). Water was pumped constantly from a fixed



Fig. 1. The location of biological samplings on the Alg@line transect (filled squares) and the location of nutrient sampling at monitoring station F3

depth (5 m) onboard the moving ship. The temperature was recorded every day (from April to December) with a spatial resolution of about 150 m using an Aanderaa thermosalinograph. The water samples for the analysis of the phytoplankton species composition were obtained weekly from 8 locations (from April to October) using an automated sampler (ISCO).

2.2. Set-up of a fuzzy logic model for predicting the *N. spumigena* bloom

A model based on fuzzy logic is developed to predict the maximum biomass value in the central part of the Gulf of Finland, taking into account the main factors (affecting aspects) that could determine the N. spumigena bloom biomass (affected aspect). The model build-up includes three steps, common to any fuzzy model approach: (1) fuzzification, in which the input data are translated to memberships of sets in qualitative terms, (2) fuzzy inference, in which a set of knowledge rules between classes of aspects are defined, and (3) defuzzification where the qualitative output of the model is translated into quantitative value. In the first step, on the basis of expert knowledge, the variables are expressed in terms of an ordered set (or classes) of qualifications, e.g. low, middle and high in the sense of influence on the affected aspect. The defined membership function represents numerically the degree to which a value of an aspect belongs to a certain class. But instead of assigning a single qualification to a variable, the fuzzy logic allows for a variable to belong to several classes with corresponding membership values. In the second step, multiple knowledge rules are applied in parallel, each with its own weight. The defuzzification step is needed to communicate the results. The model presented in this work comprises 3 relational systems: phosphate conditions, physical conditions, and maximum biomass (Fig. 2). The relational system is formed by one affected aspect and two or more related affecting aspects. The model output, the maximum biomass (maxB), is supposed to give the expected N. spumigena biomass in the upper mixed layer (UML) of the open sea. The expected maximum biomass depends on physical (surface layer temperature T_w and wind mixing tau) and phosphate conditions (excess phosphorus eP, transports by mixing tP and by upwelling upwP) (Fig. 2). The physical conditions constitute the controlling factors for N. spumigena growth. An intensive bloom does not develop if the surface layer temperature is lower than 16°C. Wind-induced turbulent mixing in the UML is regarded as a factor suppressing N. spumigena growth, because it mixes the near-surface accumulations deeper and thus leads to unfavourable light conditions (Nicklisch 1998). Small-scale shear has also been found to decrease the photosynthetic and nitrogen fixation rates of N. spumigena (Moisander et al. 2002). For the model calibration and validation the



Fig. 2. Schematic representation of the fuzzy logic model for the early forecasting of maximum *Nodularia spumigena* biomass. The input variables or aspects are shown on the left: the surface layer temperature (set valued), wind mixing (parameterised via wind stress and set valued), excess phosphorus (calculated from winter nutrient measurements), phosphate transport by mixing (parameterised via wind stress) and the phosphate transport by upwelling (parameterised via longshore wind stress component)

aspects corresponding to physical conditions are determined in the following aspect Tw is measured at the location where the sample for way: phytoplankton species composition analysis was taken (Alg@line); aspect tau is parameterised via wind stress magnitude $\tau = \rho_a C_a u^2$, where ρ_a = 1.3 kg m⁻³ is the air density, $C_a = 1.2 \times 10^{-3}$ is the dimensionless wind drag coefficient, and $u \text{ [m s}^{-1}\text{]}$ is the wind speed. As a *tau* value, the six-day median wind stress magnitude before each N. spumigena weekly sampling date is used. The phosphate conditions integrate the phosphate left over from the spring bloom and the subsequent inputs of phosphate into the UML caused by turbulent mixing and coastal upwelling events. The corresponding aspects are calculated in the manner given below. Aspect ePis calculated using the Redfield ratio (DIN:DIP=16) and the assumption is made that all DIN is utilised by phytoplankton during the spring bloom: then eP = DIP - DIN/16 [mmol m⁻³]. The phosphate input by both physical processes is considered a cumulative aspect in the model. For the model calibration and validation procedure, the phosphate input up to each weekly sampling date of N. spumigena biomass was estimated as the sum of inputs from 1 May until that sampling date. Using the calibrated model for the early prediction, all phosphate inputs by turbulent mixing and upwelling from 1 May until 15 June were summarised. To parameterise the phosphate inputs by physical processes we made rough assumptions: (1) the phosphate flux from the thermocline caused by turbulent mixing is proportional to the wind stress magnitude, and (2) the phosphate input by upwelling is proportional to the alongshore wind stress magnitude via Ekman transport. Accordingly, to calculate the phosphate transport by turbulent mixing into the UML, aspect tP, all wind events $\tau_i > 0.1$ N m⁻² with wind event duration $\Delta t > 6$ h from 1 May until the sampling date of N. spumigena are summarised: $tP = b\Sigma \tau_i$, where b is the proportionality coefficient which could be estimated on the basis of turbulence measurements (Lilover et al. 2003). The phosphate transport by upwelling, aspect upwP, is calculated by summing the Ekman transports on both coasts (Finnish and Estonian) for the period from 1 May until 3 weeks before the N. spumigena sampling date. As Ekman transport is proportional to the alongshore wind stress component, then $upwP = c\Sigma\tau_i$, where τ_i is the alongshore wind stress component which results in an Ekman transport greater than $0.5 \text{ m}^2 \text{ s}^{-1}$, and c is the proportionality coefficient. The measured biomass is calculated as the product of the measured N. spumigena biomass concentration B_m $[g \text{ ww m}^{-3}]$ and the depth of the UML h [m], assuming that the cells are distributed homogeneously within this layer. Depth h is estimated by the formula $h = 0.1 u_*/f$ (Csanady 1982), where $u_* = (\tau/\rho_w)^{1/2}$ is the friction velocity (m s⁻¹), $\rho_w = 1005$ kg m⁻³ is the water density, and $f = 1.3 \times$ 10^{-4} s⁻¹ is the Coriolis parameter. If the estimated h < 5 m, then h is set equal to 5 m.

The selection of classes ('low', 'middle', 'high' or 'very high'), the adjustment of their borders for the membership functions, and the tuning of the knowledge rules were performed by relying on expert knowledge and on trial-and-error tests. After each test before the evaluation of model performance, the data (measured and modelled) passed the growth control procedure, in which pairs of data where the modelled values of N. spumigena biomass exceed the maximum possible biomass were excluded. This procedure was included in the model calibration to avoid the use of unrealistically high modelled biomasses (e.g. as a result of a rapid rise in water temperature). The possible maximum biomass for a given sampling date is calculated by using the temperature-dependent growth rate of N. spumigena by formula $B_d = B_0 e^{kd}$, where B_d is the maximum possible N. spumigena biomass, B_0 is the biomass measured during the previous sampling, k is the water-temperature-dependent growth rate, and d is the time in days between samplings. An Arrhenius plot (lnk = A + B/T) was used to describe the growth rate temperature dependency (here the water temperature T is in degrees Kelvin). Coefficients A = 18.55 and B = -5664are determined assuming the 10°C quotient Q_{10} to be 2 and using a growth

rate of 0.4 per day at 18°C (Stolte et al. 2002, personal communication). The model performance was evaluated by the root mean square difference of the modelled and observed biomasses $(r.m.s. = (\sum_{i=1..n} (a_i - b_i)^2/n)^{0.5}$, where *n* is the number of measured values, a_i is the measured value, and b_i is the model result). Also, the coefficient of determination $CoD = 1-(\sum_{i=1..n} (a_i - b_i)^2)/(\sum_{i=1..n} (a_i - a_m)^2)$, where a_m is the mean of the measured values, was used for evaluating the tests. The *CoD* represents the portion of the variance that has been explained or accounted for by the modelled biomass; it has a maximum value of 1 or 100%. The fuzzy model presented in this paper was realised using MATLAB Fuzzy Toolbox.

3. Results

With regard to possible harmful effects, the peak biomass value of the bloom is the main concern for the public. Therefore, the maximum biomass of N. spumigena at each weekly crossing of the Helsinki-Tallinn transect was taken as a model output parameter for the model calibration. To achieve the best accordance between the calculated and observed N. spumigena biomass in the UML, the model membership functions and knowledge rules were adjusted in the model calibration using Alg@line N. spumigena biomasses, water temperatures and Kalbådagrund weather station wind data from 1997 to 2001. The measured N. spumigena biomasses from the start of the bloom development (the first half of June) to the summer maximum biomass, usually observed between the second half of July and the first half of August, were used. The best fit between the measured and simulated data (Fig. 3) is characterised by the *r.m.s.* difference of ± 2.9 g ww m⁻² and CoD 63%. The corresponding membership functions for the input parameters and the model knowledge rules applied are presented in Fig. 4 and in Table 1 respectively.

The calibrated model was tested against an independent set of data from the years 2002 and 2003 to evaluate how well the model simulations fit these data (Fig. 3). The model performance on the full data set (1997 to 2003) resulted in a r.m.s. of ± 3.3 g ww m⁻² and CoD 67%, showing that the quality of the model output did not change significantly. Although the number of data used for the model validation was small (6 pairs), it was concluded that the model had been satisfactorily calibrated.

The sensitivity of the model output parameter B (biomass) to a given model aspect k is quantified by calculating the normalised sensitivity $S_{B,k}$, defined as the fractional change in B due to a fractional increase in the value of k (Friedrichs 2001),

$$S_{B,k} = ((B_R - B_S)/B_S)/((k_R - k_S)/k_S).$$



Fig. 4. Membership functions of the input parameters used in the fuzzy model. The classes 'low', 'middle' and 'high' are depicted as follows: the solid line marks the low class, the dotted line the middle class and the dashed line the high class

Here B_R is the value of B obtained by using reference values of aspects k_R , whereas B_S is the value of B obtained by giving a certain increase to k_R , e.g. $k_S = 1.2 \ k_R$. In our case k_R is the mean value of the corresponding aspect over a 7-year-long weekly dataset, except T_w , for which $k_R = 19^{\circ}$ C. The sensitivity tests were carried out using fractional increases by 10%,

Table 1. Knowledge rules used in the fuzzy model regarding relational systems: phosphate conditions Phos (Phos is a function of aspects tP, upwP and eP), physical conditions Phys (Phys is a function of T_w and tau) and maximum biomass MaxB (MaxB is a function of Phos and Phys)

	System	n: Phos	System: Phys				
tP	upwP	eP	Phos	T_w	tau	Phys	
low	low	low	low	low	low	low	
low	low	middle	low	low	middle	low	
low	low	high	middle	low	high	low	
low	high	low	middle	middle	low	middle	
low	high	middle	middle	middle	middle	middle	
low	high	high	high	middle	high	low	
low	middle	low	low	high	low	high	
low	middle	middle	middle	high	middle	high	
low	middle	high	middle	high	high	middle	
high	low	low	middle				
high	low	middle	middle	System: MaxB			
high	low	high	high	Phys	Phos	MaxB	
high	high	low	high	low	low	low	
high	high	middle	high	low	middle	low	
high	high	high	high	low	high	low	
high	middle	low	middle	middle	low	low	
high	middle	middle	high	middle	middle	middle	
high	middle	high	high	middle	high	high	
middle	low	low	low	high	low	low	
middle	low	middle	middle	high	middle	high	
middle	low	high	middle	high	high	v. high	
middle	high	low	middle				
middle	high	middle	high				
middle	high	high	high				
middle	middle	low	middle				
middle	middle	middle	middle				
middle	middle	high	high				

20% and 1 standard deviation (SD). In the latter case the SD and the mean value of aspects were calculated over the yearly maximum values. Based on the analysis (Table 2), the modelled *N. spumigena* biomass is the most sensitive to changes in the surface layer temperature and the excess phosphorus. The variations of the modelled biomass for the increase of one input parameter by 1 SD are depicted in Fig. 5, which explains the results in Table 2 in terms of biomass. However, Laanemets et al. (2006) showed that the biomass simulation did not work without considering the contribution of aspects upwP and tP. The model presented here would

Table 2. Results of the model sensitivity analysis: (*) k_S equals 1.1 and 1.2 times the mean values of eP, tP, upwP, and tau respectively; the reference value of T_w was set to 19°C, (**) k_S is equal to the mean of yearly maximum values increased by 1 SD respectively

k	eP	tp	upwP	T_w	tau
$S_{B,k1.1mean^*}$	1.9	0.3	0.2	3.5	-0.3
$S_{B,k1.2mean^*}$	1.8	0.3	0.3	2.8	-0.3
$S_{B,kmeanofmax+SD^{**}}$	1.9	0.2	0.4	2.9	-0.4



Fig. 5. Sensitivity of the model output parameter (maximum biomass) to the increase of one input parameter by one SD (SD is calculated using the maximum biomasses from 1997–2003). The open circles mark biomass with unchanged values, the filled circles mark the biomass with an increased value of the corresponding input parameter

evidently fail to forecast the maximum biomass for the years 1997, 2001 and 2003 if the nutrient contributions by upwelling and turbulent mixing were not accounted for (Figs 6a and 6b; without considering these processes, the *r.m.s.* misfit increased from 4.1 to 8.3 g ww m⁻² and *CoD* decreased from 67 to 0%). The inclusion of one of these processes reduces the misfit to 4.3 or 4.5 g ww m⁻² and increases *CoD* to 64 or 61% respectively (Figs 6c and 6d).

The ability of the fuzzy model to forecast early the summer maximum biomass of N. spumigena (about a month before the regular bloom occurrence) was tested for the years 1997–2004. According to the model the expected bloom biomass depends on the physical and phosphate conditions.



Fig. 6. Weight of different phosphorus components in the modelled biomass, yearly maximum biomasses (a), phosphate inputs by upwelling and turbulent mixing excluded (b), only phosphate input by turbulent mixing excluded (c), only phosphate input by upwelling excluded (d)

The physical conditions for the late summer are unpredictable on 15 June (the date for the early forecast). Indeed, the water temperature in the upper mixed layer T_w on 15 June does not correlate with T_w in the late summer (correlation coefficient, -0.03). Therefore, the surface layer temperature was set to vary in the range of 14–23°C and the typical median wind speed of 5.5 m s⁻¹ for the one month period after 15 June was used. Hence, the predicted biomass is a function of the surface layer temperature. The phosphate conditions prior to 15 June include the excess phosphorus left over after the spring bloom and the calculated phosphorus input by wind mixing tP and upwelling upwP from 1 May to 15 June. Unlike the water temperature, tP and upwP on 15 June are correlated with tP and upwP at the maximum bloom time (correlation coefficients 0.64 and 0.81 respectively) and they explain on average about 70 and 82% of the variability at the maximum bloom time (Fig. 7). The results of the early prediction of the bloom biomass (biomass potential) based on phosphate conditions on 15 June (phosphate potential) are presented in Fig. 8 by open circles (note that the wind speed is constant for all years and T_w is set to 23°C). The predicted summer maximum biomasses differ strongly and show that the phosphate conditions really do differ from year to year. The realisation of the phosphate potential by N. spumigena depends on the actual surface layer water temperature (lines in Fig. 8). Both the maximum values of the measured biomasses and the corresponding water temperatures vary over a wide range (symbols in Fig. 8). In cold summers the water temperature restricts blooming (e.g. the year 2000, when the high bloom potential is not realised owing to the low water temperature). In warm summers the biomasses vary because of the different phosphate conditions (e.g. the year 2001 vs the years 1999 and 2002). In 2001 and 2002 the observed biomasses were higher than the forecast values, which points to the importance of phosphate input by physical processes after 15 June (Fig. 7). According to Fig. 7 the predicted values in general should be lower than the observed values. In this respect the year 2003 does not at first glance fit into the scheme. But on inspecting the previous week's wind data, it becomes clear that in this case the wind mixing had not been strong enough before the N. spumigena was sampled, i.e. the actual peak concentration remained in the layer above the sampling depth. Consequently, the measured value could not reflect the actual N. spumigena biomass. The year 2004 seems to be a case which cannot be explained within the framework of the suggested model and can serve as material for its further modification.



Fig. 7. The phosphate components by turbulent mixing tPand by upwelling upwP up to June 15 (dashed curves) and up to the date of the observed maximum biomass (solid curves)



Fig. 8. Early prediction of maximum *Nodularia spumigena* biomass on the basis of 1997–2004 data. The open circles on the right mark the bloom potential taking into account the phosphate conditions up to 15 June in the respective years. The lines represent the predicted maximum biomass as a function of the surface layer temperature. The dotted line represents the expected biomass when all three phosphate inputs were set to their minimum values from the period 1997–2003; the minima of inputs caused by upwelling and turbulent mixing were estimated from the annual values up to the time of the measured maximum biomass. The dashed line represents the expected biomass for the zero excess phosphorus and minimum phosphate conditions caused by upwelling and turbulent mixing. Symbols indicate the maximum measured biomass and the respective water temperature in summers 1997–2004

4. Discussion

The suggested fuzzy logic model for predicting *N. spumigena* biomass in the UML of the Gulf of Finland is based on the analysis of field data and expert knowledge of agents that are considered to be the main growth limiting factors. Analysis of the observational data has revealed that the annual maximum *N. spumigena* biomass is highly dependent on the surface layer temperature ($r^2=0.73$, p < 0.001, n = 11, 1992–2003) (Laanemets et al. 2006); temperature therefore seems to be an important environmental factor controlling the development of the bloom biomass. The latter is explicitly expressed by the presented model; sensitivity analysis of this (Fig. 5) showed the surface layer temperature to be the model's most important input parameter.

Phosphorus availability is the principal precondition for the formation of cyanobacterial blooms (e.g. Niemi 1979). According to Laanemets et al.

(2006) the regression between the excess phosphate remaining after the spring bloom and the maximum N. spumigena biomass in the UML in warm summers was good ($r^2=0.61$, p < 0.05, n = 8; 1992–2003). Nevertheless, it was also shown that in some years the annual maximum biomasses of N. spumigena cannot be explained by the excess phosphate only. The presented simulation results indicate that the best fit can be achieved if the phosphate inputs by turbulent mixing and upwelling events are also taken into account; Larsson et al. (2001) stated these to be important phosphorus sources for N. spumigena. The estimates based on turbulence and nutrient measurements showed that a wind event lasting for a day with a mean speed of c. 11 m s⁻¹ could result in an increase of phosphate concentration by 0.03 mmol m^{-3} in the UML (Lilover et al. 2003). In the years from 1997 to 2004, strong wind events were observed most frequently in 1999 and 2000 (10 events from 1 May to 15 July) and less frequently in 2003 and 2004 with only 3 events per summer. Strong wind events differ in their duration and strength: both characteristics are taken into account in the tP aspect. Thus, 5–10 strong wind events can cause the phosphate input into the UML to be comparable with the minimum excess phosphorus $(0.33 \text{ mmol m}^{-3})$ observed during the period studied. The few field measurements in the upwelling zone in the western Gulf of Finland have revealed a relatively high phosphate concentration compared with the nitrate concentration (ratio about 1), resulting in a vertical separation of the phosphacline and nitracline in the thermocline (Kononen et al. 2003, Laanemets et al. 2004, Vahtera et al. 2005). Despite the crude parameterisation of both phosphate inputs via the wind stress only, the best calibration fit of the model was achieved by including both sources (Fig. 3).

Early prediction of the summer maximum N. spumigena biomass is based on the measured excess phosphate and the parameterised input of additional phosphate by physical processes between the spring bloom and 15 June. In most cases, the prediction lines for years with different phosphate conditions were relatively close to the measured maximum biomasses at the corresponding temperatures; nevertheless, the measured biomass was still higher than the predicted value (Fig. 8). The latter indicates, according to Fig. 7, the importance of the additional phosphate input after 15 June. In the warm year of 1999, the phosphate conditions changed less after 15 June than in the other warm years of 2001 and 2002 (Fig. 7), and only in this case was the prediction line close to the observed biomass (Fig. 8). Simulations were also performed for two prescribed phosphate conditions: (1) all three phosphate inputs were set to the minimum values from the period 1997–2003, and (2) the excess phosphate was set to zero, while retaining the minimum values of the other inputs (Fig. 8). The model runs showed that a *N. spumigena* bloom (defined here as a biomass >5 g ww m⁻²) could be expected even if all phosphate inputs had minimum values and the surface layer temperature exceeded 18°C. So, given the present phosphate conditions in the Gulf of Finland in warm summers, *N. spumigena* blooms should be rather a common phenomenon.

In cases when the excess phosphate is set to zero and the other phosphate inputs are kept at their minimum values, blooms will rely on the phosphates brought into the surface layer by mixing and upwelling (Fig. 8) and are to be expected only in extraordinarily warm summers ($T_w > 21^{\circ}$ C).

Summing up, we conclude that despite relying only on a few widely accessible input data (winter DIN and DIP, wind), the model permits the early prediction (about a month before the usual time of the bloom occurrence) of the annual maximum *N. spumigena* biomass with respect to different surface layer temperatures (weather scenarios).

Acknowledgements

The N. spumigena biomass concentration and temperature data on the Helsinki-Tallinn transect were kindly provided by the Alg@line project (Finnish Institute of Marine Research, Uusimaa Regional Environment Centre, City of Helsinki Environment Centre, Estonian Marine Institute). The Finnish Institute of Marine Research kindly provided the nutrient data and the Finnish Meteorological Institute (Kalbådagrund weather station) supplied the wind data. Likewise, we are grateful to the community of the EC project HABES (contract EVK2-CT-2000-00092) for introducing us to the fuzzy logic modelling of biological processes. The discussions with Willem Stolte on the growth control procedure and the Arrhenius plot method, as well as his providing us with the relevant coefficients are greatly appreciated. We also thank the anonymous referees for their valuable comments on the manuscript. The research of M.-J. Lilover was supported by a grant received through the Enlargement Action of the EU Commission 6th Framework Programme.

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