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### Monitoring and prediction of phytoplankton dynamics in the North Sea

Blauw, A.N.

**Publication date**

2015

**Document Version**

Final published version

[Link to publication](#)

**Citation for published version (APA):**

Blauw, A. N. (2015). *Monitoring and prediction of phytoplankton dynamics in the North Sea*. [Thesis, fully internal, Universiteit van Amsterdam].

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# Chapter 5

## The use of Fuzzy Logic for Data Analysis and Modelling of European Harmful Algal Blooms: Results of the HABES Project

### ABSTRACT

In the project Harmful Algal Blooms Expert System (HABES) fuzzy logic was applied to model blooms of *Nodularia spumigena*, *Dinophysis spp.*, *Alexandrium minutum*, *Karenia mikimotoi* and *Phaeocystis globosa* at various European sites. The fuzzy logic technique was useful in making integrated analyses of interacting physical and biological factors involved in HABs. A basic knowledge of HAB formation and sufficient data are a prerequisite for successful bloom prediction.

*This chapter is based on the paper: Blauw, A.N., Anderson, P., Estrada, M., Johansen, M., Laanemets, J., et al., 2006. The use of fuzzy logic for data analysis and modelling of European harmful algal blooms: results of the HABES project. African Journal of Marine Science 28: 365-369.*

## 5.1 INTRODUCTION

Harmful algal blooms (HABs) are responsible for human health problems and substantial economic losses every year in aquaculture, due to shellfish toxicity and mass fish mortality. Furthermore, some HABs lead to closure of beaches to tourists and have devastating effects on aquatic ecosystems. Prediction of blooms and insight in the impact of human activities on the frequency and intensity of blooms are needed to support water managers in the planning and deciding on appropriate mitigating measures. For management purposes it is important to understand which are the main factors controlling the risk of HABs. Models provide a helpful tool in efforts to relate various processes and in evaluating the relative importance of each of these processes. Common modelling approaches are statistical models and numerical models. Statistical models tend to be tailored to the specific dataset used for its development and do not provide a generic theoretical framework. The use of numerical models for operational modelling requires a detailed understanding of the processes involved and sufficiently detailed input data, which are not always available. Statistical models require large datasets as well.

An alternative modelling approach is fuzzy logic. The concept of 'fuzzy logic' was introduced by Zadeh (Zadeh, 1965) as an extension of Boolean logic to enable modelling of uncertainty. Fuzzy logic introduces a concept of partial truth values, that lie in between 'completely true' and 'completely false'. The knowledge is typically represented in terms of IF-THEN rules. An example is: IF A AND B THEN C. The truth value of the rule's premise describes to what degree the rule applies in a given situation. An advantage of modelling HAB dynamics with fuzzy logic is the possibility to combine qualitative and (partial) quantitative knowledge of physiological and physical processes with a certain degree of uncertainty within the available data set (Droesen 1996). Fuzzy logic can be seen an intermediate method between fully deterministic models and fully empirical models, where a conceptual understanding of phenomena reduces the amount of field data needed. A successful example of this approach is available for prediction of floating scums of *Microcystis* in fresh water (Ibelings et al. 2003).

This paper evaluates the application of fuzzy logic modelling of HABs in various European pilot study areas that were included in the HABES project (Harmful Algal Blooms Expert System). The final report of the project and other project deliverables are publicly available through the project website [www.habes.net](http://www.habes.net) until at least 2008.

## 5.2 MATERIAL AND METHODS

Fuzzy logic models in different European pilot areas for different harmful algal species were developed in the following steps:

1. Construction of a conceptual model for each species, based on literature review and expert knowledge. The conceptual model is a scheme representing the hypothesized relations between key input variables, intermediate variables and the final output parameter: the probability of a harmful algal bloom event. As an example the conceptual model for *Nodularia spumigena* is presented in Figure 5.1.
2. Quantification of the relations in the conceptual model as fuzzy logic knowledge rules by means of data analysis and expert knowledge. For example, the relation between surface layer temperature, wind mixing and suitable physical conditions for *Nodularia* blooms can be quantified with the following (simplified) knowledge rule:

IF surface layer temperature is sufficiently high (above 14.5-19°C); AND

IF wind mixing is sufficiently low (below 5-35  $\text{Nm}^{-2}$ ); THEN

Physical conditions are suitable for blooms of *Nodularia spumigena*.

In the knowledge rule the thresholds for temperature and wind mixing are not single values but ranges, representing gradual (fuzzy) transitions between suitable and unsuitable conditions.

3. Validation of the model results with available data, whenever possible for other years or other pilot areas than used for step 2.

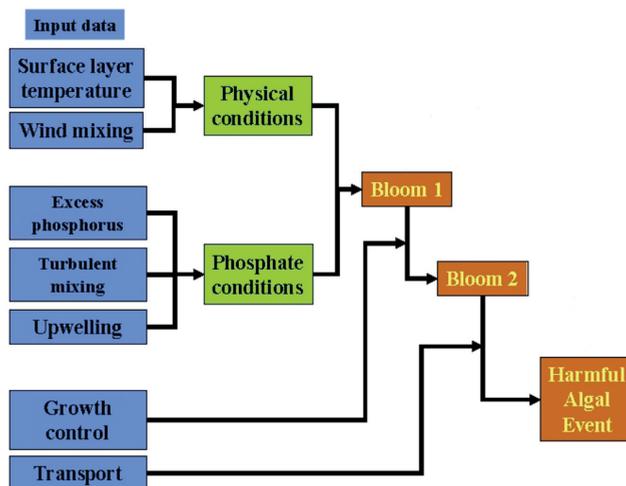


Figure 5.1: Conceptual model for *Nodularia spumigena*.

## 5.3 RESULTS

### 5.3.1 *Nodularia spumigena* in the Gulf of Finland

In the model for *Nodularia spumigena* (Laanemets et al. in press) it is assumed that the timing and intensity of blooms is determined mainly by the water temperature, wind speed (as a proxy for water column stability) and the availability of phosphorus. In turn, the availability of phosphorus is determined by excess phosphorus that is left over after the spring bloom and by additional phosphorus supply that is mixed across the pycnocline into the upper mixed layer by wind-induced turbulence and upwelling. The relation between wind speed and turbulent mixing of phosphorus across the pycnocline is quantified based on field experiments (Lilover et al. 2003, Lilover and Laanemets 2003). The level of upwelling is quantified based on daily observed temperature differences along the ferry transect between Helsinki and Tallinn. A temperature-dependent maximum growth rate restricts the rate of biomass increase. Assuming that blooms generally develop in the central part of the Gulf of Finland, transport tables have been set up for different locations along the coast to determine when blooms will reach the coast under different wind conditions, based on numerical model simulations. Figure 5.2 shows the validation results for *Nodularia spumigena* in the Gulf of Finland.

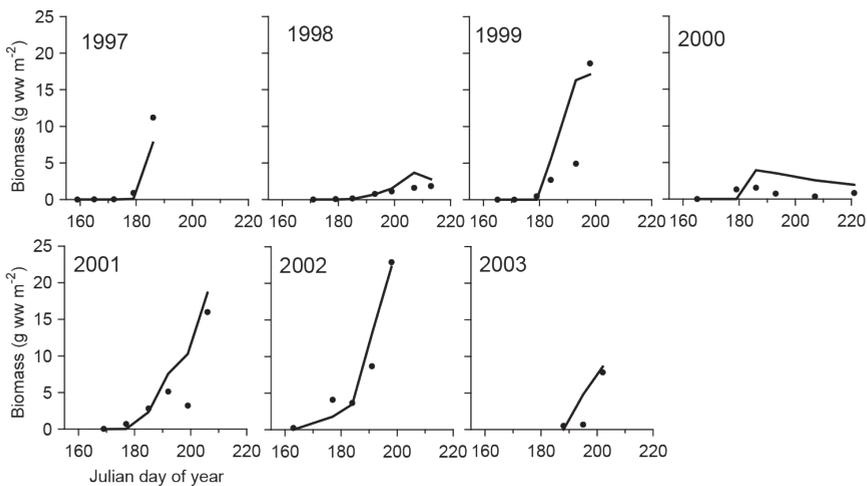


Figure 5.2: The measured (black dots) and modelled (bold line) *N. spumigena* biomass in the water column in the Gulf of Finland for years from 1997 to 2003.

### 5.3.2 *Nodularia spumigena* in the Baltic Sea

The same model that has been developed for *Nodularia* in the Gulf of Finland has been applied and validated for the Baltic Sea. Due to differences in data availability and hydrography the quantification of the input parameters needed to be adapted for the Baltic Sea. The model results have been validated with field observations at different locations (see for example Figure 5.3) and with satellite images showing floating layers of *Nodularia*.

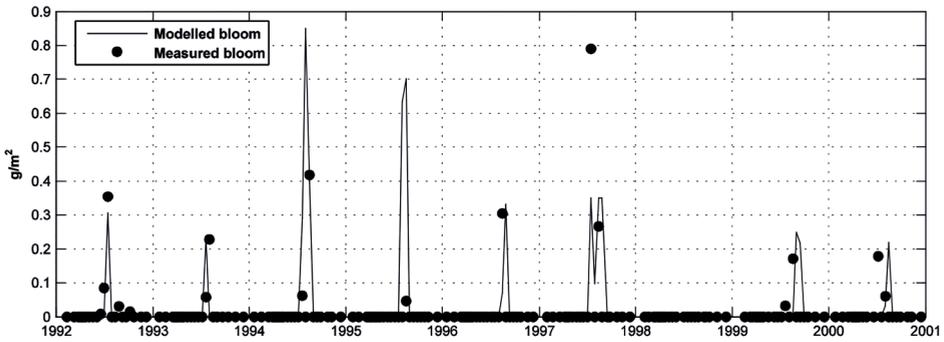


Figure 5.3: Measured (dots) and modelled (line) *N. spumigena* biomass in the water column in the Baltic Sea from 1992 to 2001.

### 5.3.3 *Dinophysis spp.* and *Karenia mikimotoi* in Irish coastal waters

In Bantry Bay (Ireland), the inflow of *Dinophysis acuta*, *Dinophysis acuminata* and *Karenia mikimotoi* was shown to be associated with the wind-driven exchange of waters with the coastal current (Raine et al. 1993). A model based on this wind-driven exchange and the presence of blooms in the coastal current during summer has been validated with historical data. The model satisfactorily predicted harmful events in Bantry Bay (Table 5.1). Only in 1997, a toxic bloom was predicted with high probability but was not observed.

Table 5.1: Validation results for Bantry Bay for 1990 – 2002: years with and without toxic blooms observed and predicted (in hind-cast).

	No toxic event observed	Toxic event observed
No toxic event predicted	1992, 1996	
Toxic event predicted	1997	1991, 1998 ( <i>Karenia</i> ) 1994, 1995, 2000 2001, 2002 ( <i>Dinophysis</i> )

### 5.3.4 *Dinophysis* spp. in Swedish and Dutch coastal waters

The Irish *Dinophysis* model may also be applicable for *Dinophysis* spp. in coastal currents along the Swedish and Dutch coasts. Godhe et al. (2002) showed that a toxic bloom in a Swedish fjord could be attributed to import from the coastal current. However, insufficient historic data were available along this coast to quantify the relation between wind conditions and water exchange between the fjords and the coastal current. Another reason that restricts the applicability of the Irish *Dinophysis* model in Sweden and the Netherlands is that *Dinophysis* is not present in the coastal current all summer, as in Ireland. Prediction of the development of blooms in the coastal current requires a more complicated model, including phenomena that are not yet understood.

### 5.3.5 *Alexandrium minutum* in Barcelona coastal waters

Since only limited understanding was available for building knowledge rules, the fuzzy logic model for *A. minutum* was based on hypotheses regarding the effect of dispersion rates, nutrients and fresh water runoff, and on historical data on the susceptibility of seasonal periods and geographical localities to *A. minutum* blooms. In Barcelona coastal waters, the highest cell concentrations of *A. minutum* tend to occur during late winter. Once a bloom is initiated, overall nutrient load in each location, water residence times and duration of relatively calm weather are likely to be important in determining the maximum cell concentrations attainable. Water confinement may increase due to man-made structures such as harbours or littoral fronts caused by fresh water inputs. Observation of such littoral fronts with continuous video monitoring made clear that their duration is short (around one day). Hydrographical markers (such as salinity gradients) were more long-lived, so that the possibility that littoral fronts could have an effect on bloom formation could not be discarded. The model performed well in predicting the low and high population densities of *A. minutum*, but tended to exaggerate the observed bloom intensity.

### 5.3.6 *Phaeocystis globosa* in English coastal waters

In western English Channel coastal waters off Plymouth, *Phaeocystis globosa* blooms occur every year in spring with a duration of two to three weeks. However, there is large interannual variability in the intensity of the blooms. Data analysis showed that bloom intensity was mainly determined by the amount of river runoff and associated nutrient flux from the nearby river Tamar. Also, in some years, elevated concentrations of chlorophyll-*a* (due to early diatom growth) in winter were followed by much lower intensities of the *Phaeocystis* blooms in the following spring (e.g. 2000). A fuzzy logic model simulating bloom intensity based on river nutrient flux and winter/spring irradiance levels gave good results (see Figure 5.4).

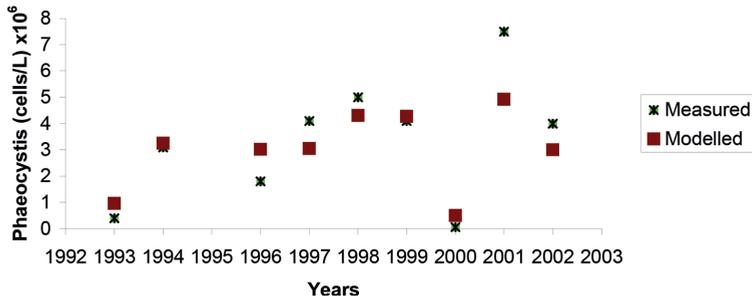


Figure 5.4: Measured and modelled *Phaeocystis* peak bloom intensity in English coastal waters.

### 5.3.7 *Phaeocystis globosa* in Dutch coastal waters

The model for *Phaeocystis globosa* in Dutch coastal waters comprises separate submodels for 1) bloom timing, 2) bloom duration, 3) bloom intensity and 4) foam intensity. The bloom timing is assumed to be determined by the underwater light climate, which in turn is controlled by transparency and mixing layer depth. Wind speed, which affects both sediment resuspension and mixing layer depth proved to be a useful indicator. Monitoring frequency in Dutch coastal waters was insufficient for a good analysis of interannual variability of bloom duration and intensity. However, analysis of long term median bloom intensities between different locations showed a clear relation with salinity and dissolved inorganic nitrogen and phosphorus concentrations in winter. As these three parameters are correlated it is not possible to distinguish between their effects. Bloom duration could be roughly approximated by water temperature and irradiance in early spring. The resulting model was calibrated and validated with monitoring data from 1990 – 2002. Figure 5.5 shows the results for *Phaeocystis* biomass for 1996 – 2001. The foam submodel simulates foam intensity during *Phaeocystis* blooms based on wind speed and direction. In the years 1999 – 2001 absence of nuisance foam on spring days was predicted correctly in 88% of the days and presence in 90% of the days.

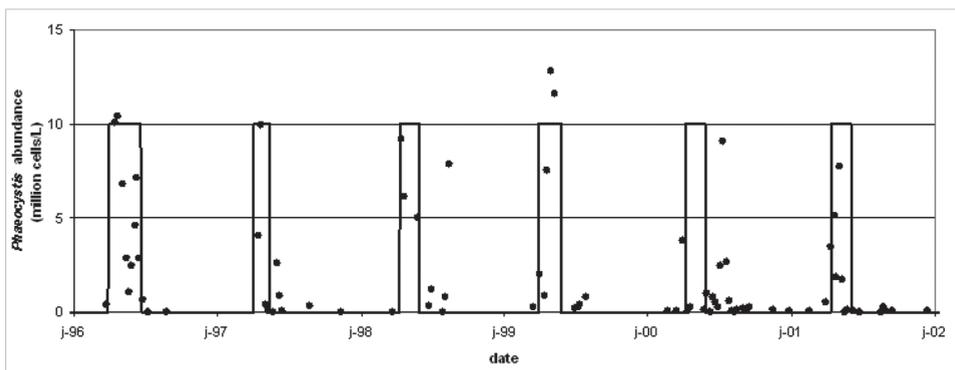


Figure 5.5: Observed (points) and simulated (line) *Phaeocystis* abundance in Dutch coastal waters for the years 1996 – 2001.

## 5.4 CONCLUSIONS

During the model development it was evident that constructing a fuzzy logic model was not difficult, provided that sufficient knowledge and data were available. However, in many cases the understanding of the species dynamics and ecosystem functioning was not sufficient at the start of the project to be easily quantified and translated into fuzzy logic knowledge rules. The data-analysis has considerably increased the understanding of the species and the interactions with their physical environment. The fuzzy logic modelling technique proved to be a useful method to make an integrated analysis of the interacting physical and biological factors involved in HAB dynamics. The approach is especially useful for modelling the development of blooms that can be described as a combination of straightforward cause-effect relations. Complex phenomena, such as feedback mechanisms or slow biomass increase depending on a time series of irradiance or transport of patches at sea, are difficult to implement in fuzzy logic.

The model for the Gulf of Finland has been run in operational mode in 2004 and preparations are being made for a future operational service through internet. In the Netherlands knowledge gained on bloom timing has been implemented in an existing numerical model, to enable modelling of not only bloom development but also bloom transport. This model is part of a harmful algal bloom early warning system, that has been tested in hindcast for 2001 and 2003 and should be operational in spring 2006. The model for SW Ireland is operational at the website of the Marine Institute ([www.marine.ie](http://www.marine.ie)) since summer 2005.

## ACKNOWLEDGEMENTS

We gratefully acknowledge the financial Support from EU 5th Framework Programme for the HABES project. We thank colleagues and institutes that kindly provided data for analyses and modelling: PML, Alg@line, M. Vila, meteorological institutes in all countries participating, Swedish routine monitoring and Irish, Dutch and Swedish shellfish monitoring institutes. We thank two reviewers for their valuable comments on the manuscript. Last but not least we would like to thank other participants and contributors to the HABES project: L. Arin, R. Autio, D. Blasco, Q. Chen, G. Hansen, C. Holeton, A. Iriarte, B. Karlson, O. Lindahl, M. Llover, F.J. Los, G. McDermott, U. Raudsepp, W. Stolte, J. Strickner, R. Uittenbogaard and L.P.M.J. Wetsteyn.