Harmful Algae 8 (2008) 70–76

Contents lists available at ScienceDirect

Harmful Algae

journal homepage: www.elsevier.com/locate/hal

How well can we forecast high biomass algal bloom events in a eutrophic coastal sea?

J. Icarus Allen [a,*], Timothy J. Smyth [a], John R. Siddorn [b], Martin Holt [b]

[a] Plymouth Marine Laboratory, Prospect Place, West Hoe, Plymouth PL1 3DH, UK
[b] Met Office, Fitzroy Road, Exeter, Devon EX1 3PB, UK

ARTICLE INFO

Article history:
Received 1 January 2007
Received in revised form 22 July 2008
Accepted 1 August 2008

Keywords:
Algal blooms
Model skill
North Sea
Ocean colour
Ocean forecast

ABSTRACT

High biomass algal bloom events are a characteristic of eutrophic coastal waters; these may result both in ecosystem degradation and economic loss. We present a skill evaluation of a coupled hydrodynamic ecosystem model of the NW European shelf for predicting bloom events based on a comparison with satellite chlorophyll estimates. By setting thresholds to define bloom events we use a binary classification system to generate maps showing the probability a model bloom prediction is correct. Model and satellite data limitations are discussed along with the application of this method to forecasting specific harmful algal species.

1. Introduction

A common characteristic of eutrophic aquatic ecosystems is nutrient enrichment of the water column, with subsequent enhanced growth of phytoplankton, leading to distortion of foodwebs and degradation of water quality (e.g. OSPAR, 1998). These increases in total algal biomass can lead to undesirable effects such as oxygen depletion from the decay of biomass, suffocation of fish, deleterious effects on benthic biomass and enhanced biomass of toxic algal species. The result is poor energy transfer to higher trophic levels. An extensive literature exists on these subjects and details of the influence of enhanced nutrients on harmful algae can be found in for example GEOHAB (2006), Anderson et al. (2002) and references within. Clearly there is a strategic imperative to be able to forecast algal bloom occurrence.

The NW European shelf, can be divided into two regions (Fig. 1), the north and west of the region is characterised by seasonally stratified, optically clear mesotrophic water and the south and east is characterised by tidally well mixed, optically complex eutrophic waters, in particular the southern North Sea, Irish Sea and English Channel. The UK National Centre for Ocean Forecasting (NCOF) has established a pre-operational ecosystem model of this region, based on POLCOMS-ERSEM. This model is run every week in a 7-day rolling hindcast (http://www.met-office.gov.uk/research/ncof/mrcs/browser.html). While ERSEM is a relatively complex ecosystem model, describing four phytoplankton functional types it does not resolve individual species.

There are a number of HAB species found regularly in northern European waters. They are a disparate group, with examples coming from all of the major phytoplankton classes. Their effects are wide ranging from nuisance blooms (which produce foam and are aesthetically unappealing but have no major direct impacts) to high biomass blooms, which lead to anoxia and related effects, to ichthytoxic blooms which kill fish, and may have large direct economic impacts, to blooms which produce toxins which are subsequently bio-accumulated in shellfish and thus have health and economic impacts. Shellfish poisoning in European waters comes in three major types, defined by their impacts upon human consumers; Paralytic Shellfish Poisoning (PSP), Diarrhetic Shellfish Poisoning (DSP) and Amnesic Shellfish Poisoning (ASP). Some major genera implicated in harmful events in European waters are shown in Table 1. This list is not exhaustive and other genera exist that are potentially problematic. For instance the LIFEHAB workshop report (LIFEHAB 2001) lists more than 25 diatom species found in European waters that are, or have the potential to be, toxic, of which nine are species of Pseudo-nitzschia.

Currently there are few heuristic models capable of simulating aspects of the processes controlling specific harmful algal species,

* Corresponding author at: PML, Prospect Place, West Hoe, Plymouth PL1 5LT, UK. Tel.: +44 1752 633100.
E-mail address: jia@pml.ac.uk (J.I. Allen).

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doi:10.1016/j.hal.2008.08.024

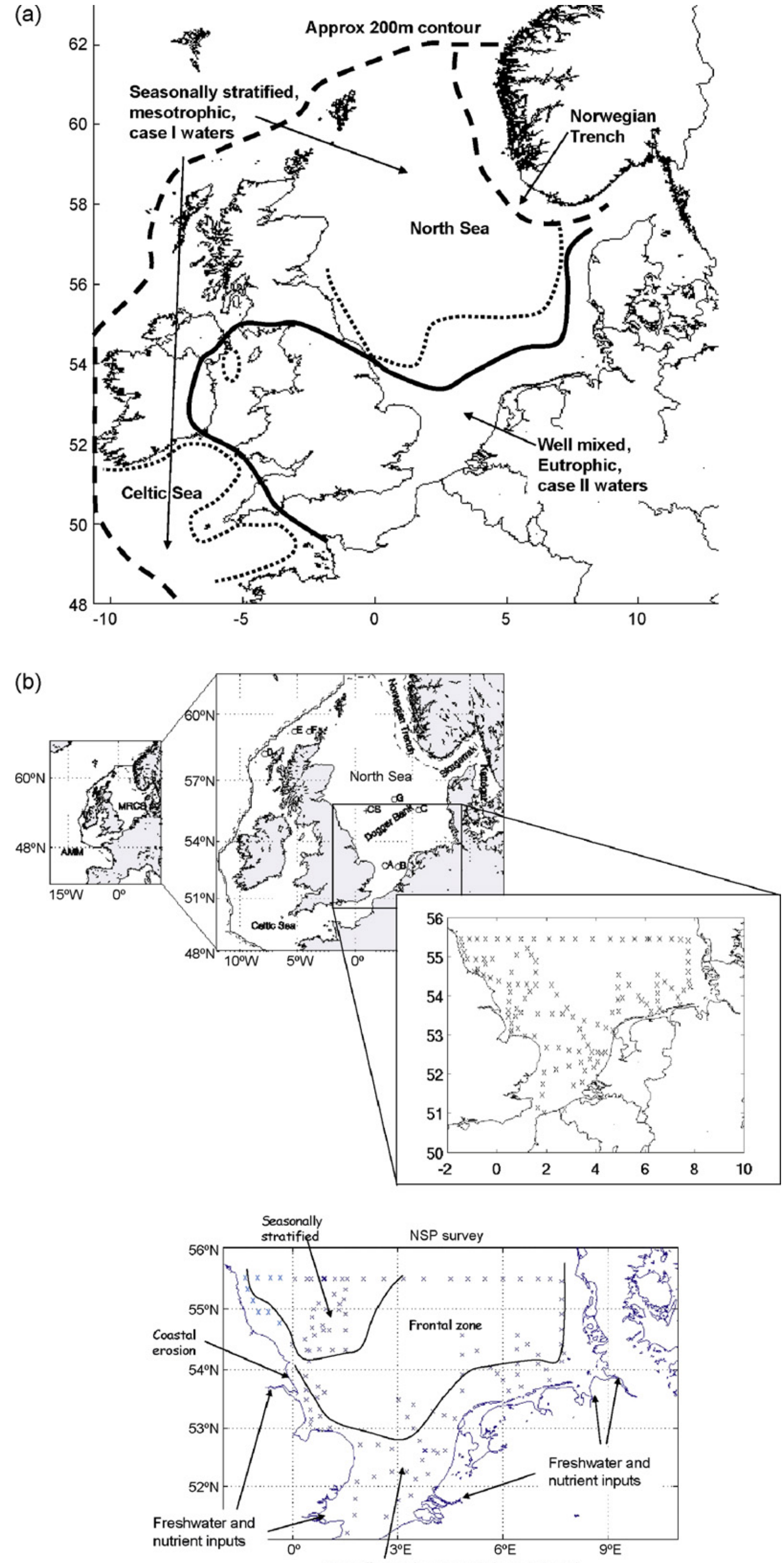

Fig. 1. (a) Map of the study region. The thick dashed line denotes the 200 m contour on the shelf break and the model boundary. The thin dotted lines indicate the approximate position of the seasonally stratified tidal mixing fronts in the region. (b) A schematic diagram of the functional groups and linkages in the pelagic components of the ERSEM model.

for example, *Phaeocystis* (Lancelot et al., 2007; Ruardij et al., 2005), *Pfiesteria* (Hood et al., 2006) and *Pyrodinium* (Villanoy et al., 2006). The forecast modelling of harmful algal blooms is in its infancy and the starting point in evaluating the usefulness or otherwise of models such as POLCOMS-ERSEM for HAB prediction is to quantify the ability of the model to simulate high biomass algal blooms.

Satellite observations of ocean colour provide extensive spatio-temporal data coverage of the distribution of chlorophyll, which in

Table 1
Some important plankton genera that cause problems in European coastal waters.

Organism	Effect	Areas with major HAB problems
Dinoflagellates		
Alexandrium	PSP, high biomass	All European coasts, except Bay of Biscay, southern North Sea and Baltic Sea
Dinophysis	DSP	Europe wide
Karenia	Ichthyotoxic	Skagerrak, Kattegat, Celtic Sea, western English Channel, central and northern North Sea, Bay of Biscay
Diatoms		
Pseudo-nitzschia	ASP	Europe wide
Flagellates		
Phaeocystis	High biomass, foam production	North Sea, English Channel, northern Norwegian fjords
Chattonella	Ichthyotoxic, high biomass	Skagerrak, North Sea coasts of Denmark, Germany and the Netherlands

Adapted from the LIFEHAB workshop report.

turn indicate the presence of large algal blooms. The aim of this paper is to assess the models ability to predict large algal blooms. We present a technique for determining the probability that the model correctly predicts a bloom event, along with a brief discussion of the sources of model errors and the generic application of the method to bloom prediction.

2. Methods

2.1. Model

The Medium Resolution Continental Shelf (MRCS) model is a hindcasting/forecasting system (Siddorn et al., 2007). It is based on a coupled 3D hydrodynamic and ecosystem model (the Proudman Oceanographic Laboratory Coastal Ocean Modelling System coupled with the European Regional Seas Ecosystem Model POLCOMS-ERSEM; Allen et al., 2001; Holt et al., 2004), set up on a 1/10° longitude by 1/15° latitude horizontal grid (~7 km) and 20 s-levels (Song and Haidvogel, 1994) in the vertical with boundaries following the North-West European Continental Shelf break (approximate along the 200 m isobath, except for the Norwegian Trench; Fig. 1a). Boundary forcing for temperature, salinity, currents and sea surface elevation is obtained from a 1/6° longitude by 1/9° latitude (~12 km) Atlantic Margin Model, which is nested in the Met Office's FOAM system (Bell et al., 2000). An averaged annual cycle is used for boundary conditions since the operational system has not simulated the period of interest here. The model includes the density evolving physics of POLCOMS (Holt and James, 2001) and a size-fractionated SPM sub-model (Holt and James, 1999), coupled with the biogeochemical processes of ERSEM (Blackford et al., 2004; Baretta et al., 1995); Fig. 1b, is a schematic of the pelagic model. ERSEM is a functional group model and has one bacteria, four phytoplankton and three zooplankton pelagic functional groups. It has a fully resolved diurnal cycle, variable carbon to chlorophyll ratios and independent nutrient pools for carbon, nitrogen, phosphorous and silicate. Coupled with the pelagic model is a benthic model to give not only detailed process information of the benthic ecosystem but also a well defined nutrient coupling between the benthic and pelagic systems. Full details of the model experiment are given in Siddorn et al. (2007).

2.2. Satellite data

Satellite data was acquired from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua ocean colour sensor as pre-processed level 2 chlorophyll-a (O'Reilly et al., 1998) individual 1 km resolution passes within the model domain. These were then projected (Mercator), mapped and weekly chlorophyll composites produced. The weekly satellite composites were then re-sampled onto the same grid as the MRCS model domain using a 14 pixel moving window median filter.

2.3. Statistical methods

We can assess model skill by using the predictive power of a binary classification system as a discrimination threshold is varied. Brown and Davis (2006) provide a detailed and accessible tutorial of these methods. The basis is a simple "yes" or "no" decision, based on the comparison of two independent information sets (in our case satellite retrievals and model) with respect to a threshold value. The aim is to assess how well a test (model) can discriminate between two discrete observed outcomes (e.g. harmful algal bloom). The perfect model is one where all the points in a scatter diagram of model vs. data lie on the $x = y$ line. The threshold criteria (t) set divides the data into two parts; by then comparing it with the model using the same threshold we can assess model data similarity at that threshold. This effectively assesses the model ability to discriminate that threshold. The decision process has four possible outcomes for each trial, either correctly positive (CP), correctly negative (CN), incorrectly positive (IP) or incorrectly negative (IN). The perfect model will only give CP and CN outcomes; the more scatter there is in the model–data relationship the more IP and IN conditions will occur and the worse the model performance is judged to be. By varying the threshold across the full range of observations, we obtain a non-parametric measure of the models ability to simulate a given variable, which can be then compared directly with other simulated variables. The classification rate for n samples is defined as

$$\mathrm{CR} = \frac{\mathrm{CP} + \mathrm{CN}}{n} \tag{1}$$

The decision process can be further assessed by calculating the correct negative fraction (CNF) and the correct positive fraction (CPF).

$$\mathrm{CNF} = \frac{\mathrm{CN}}{\mathrm{CN} + \mathrm{IP}}, \quad \mathrm{CPF} = \frac{\mathrm{CP}}{\mathrm{CP} + \mathrm{IN}} \tag{2}$$

CNF and CPF express the fraction of negative and positive events, which were correctly determined. These values are independent of the actual numbers of positive and negative events in the trials. Decisions based on CPF and CPN are estimators of probabilities of decisions conditioned on events: i.e., if a positive event (a bloom) has occurred what is the probability the correct decision has been made? While these probabilities are useful they do not address the fundamental question, if a positive decision is made what is the probability that the decision is correct. The

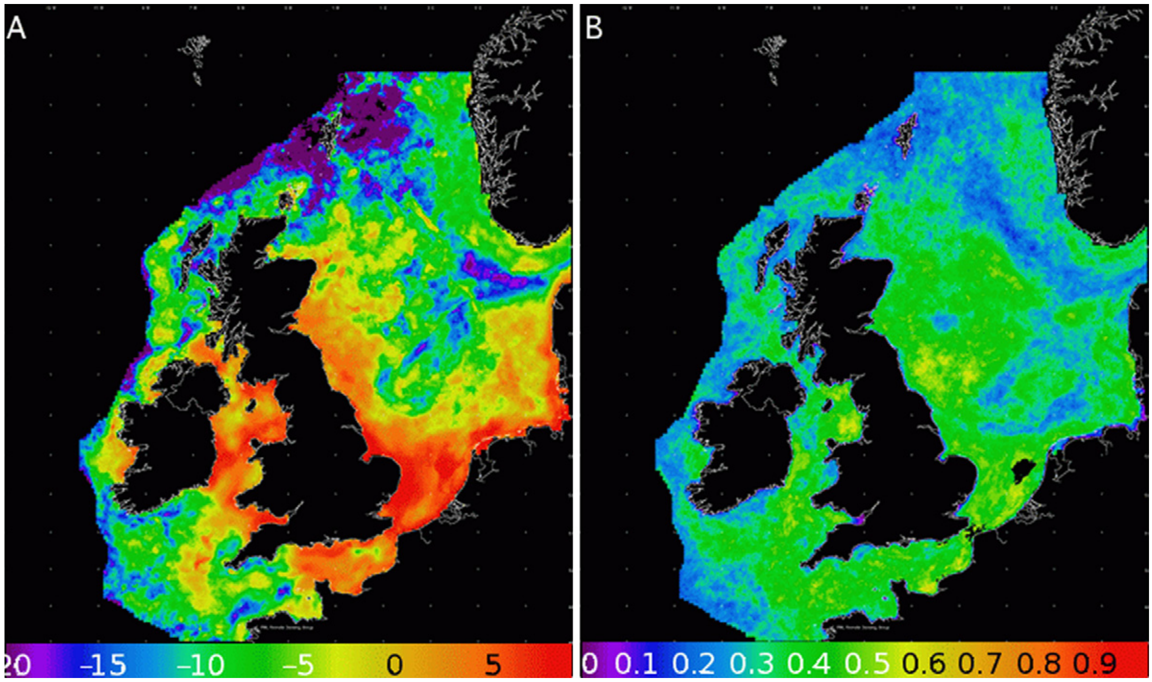

Fig. 2. (a) Percentage bias (the sum of model error normalized by the data) and (b) the classification rate for each pixel; computed from the comparison of weekly composites of MODIS Aqua chlorophyll and simulated chlorophyll for 2005. Negative bias indicates model overestimates chlorophyll. Pbias $= \sum_{n=1}^{N}(D^n - M^n)/\sum_{n=1}^{N} D^n \times 100$ D = data value, M = model value.

positive predictive value (PPV) and negative predictive value (NPV) can be expressed as (see Brown and Davis (2006) for the theoretical background and derivation).

$$\mathrm{PPV} = \frac{\mathrm{CP}}{\mathrm{CP}+\mathrm{IP}}, \quad \mathrm{NPV} = \frac{\mathrm{CN}}{\mathrm{CN}+\mathrm{IN}} \tag{3}$$

Values of PPV and NPV can range between 0 and 1, reflecting the intrinsic power of the decision; high values indicating a decision can be trusted, low values suggesting the decision should be regarded with scepticism.

To establish thresholds we have calculated the mean chlorophyll concentration for each pixel over the period 2004–2005 from the satellite weekly composites. The thresholds for a bloom are set as (i) the mean chlorophyll concentration and (ii) the mean plus 50%, for each individual pixel, to discriminate small and large bloom events, respectively.

3. Results

The distribution of the percentage bias in the model and the classification rate when compared with MODIS Aqua chlorophyll is illustrated in Fig. 2. The bias map (Fig. 2a) shows some clear trends, the model systematically overestimates chlorophyll concentrations along the ocean boundaries and in the stratified regions and systematically underestimates biomass in the highly eutrophic waters of the Irish Sea and the southern North Sea. The classification rate map (Fig. 2b) is quite similar in structure to the bias map; regions of poor performance (CR < 0.3) corresponding with regions of high negative bias (model overestimation) resulting in large numbers of false positive predictions. In terms of classification rate the model skill is best in the eutrophic waters, and the stratified central North Sea and western English Channel, achieving rates of 40–60%.

Basic error statistics have been calculated for model data misfit of the weekly composites for chlorophyll in 2005 (2004 shows similar behaviour). We illustrate the temporal evolution of model errors made by plotting the square of the correlation coefficient against the root mean square error (RMSE, Fig. 3) which gives a crude estimation of model skill. In winter there is limited forecast skill ($r^2 \sim 0.3$), but as we move into spring it decreases markedly. In April the r^2 is almost zero implying very little skill; this is probably a consequence of errors in the timing of the spring bloom. During the summer the model explains up to 50% of the variability in the data ($r^2 \sim 0.5$ in August), then the skill steadily deteriorates until by November it is close to zero. This deterioration in skill may be in part due to prolonged thermal stratification (Holt et al., 2005).

Fig. 4 shows maps of the spatial probability distribution for PPV and NPV being correct for the two thresholds of the annual mean chlorophyll (panel A and C) and 50% above the pixel mean chlorophyll (panel B and D) for each pixel. These maps indicate on a pixel by pixel basis the ability of the model to discriminate thresholds of chlorophyll concentration. When the threshold is set to the mean, 40–50% of the model bloom predictions are correct over most of the domain (Fig. 4a). There are patches where the skill

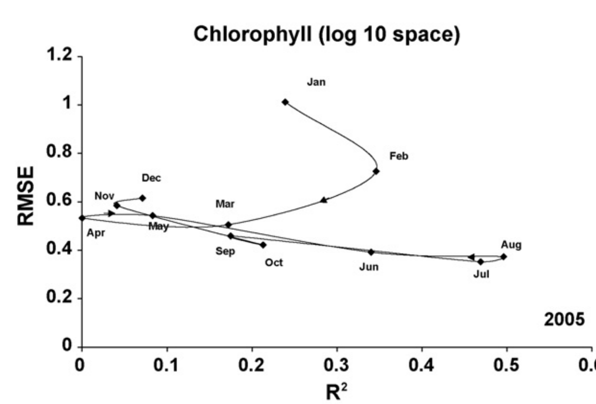

Fig. 3. Phase space plots of the monthly variation in errors in chlorophyll in 2005.

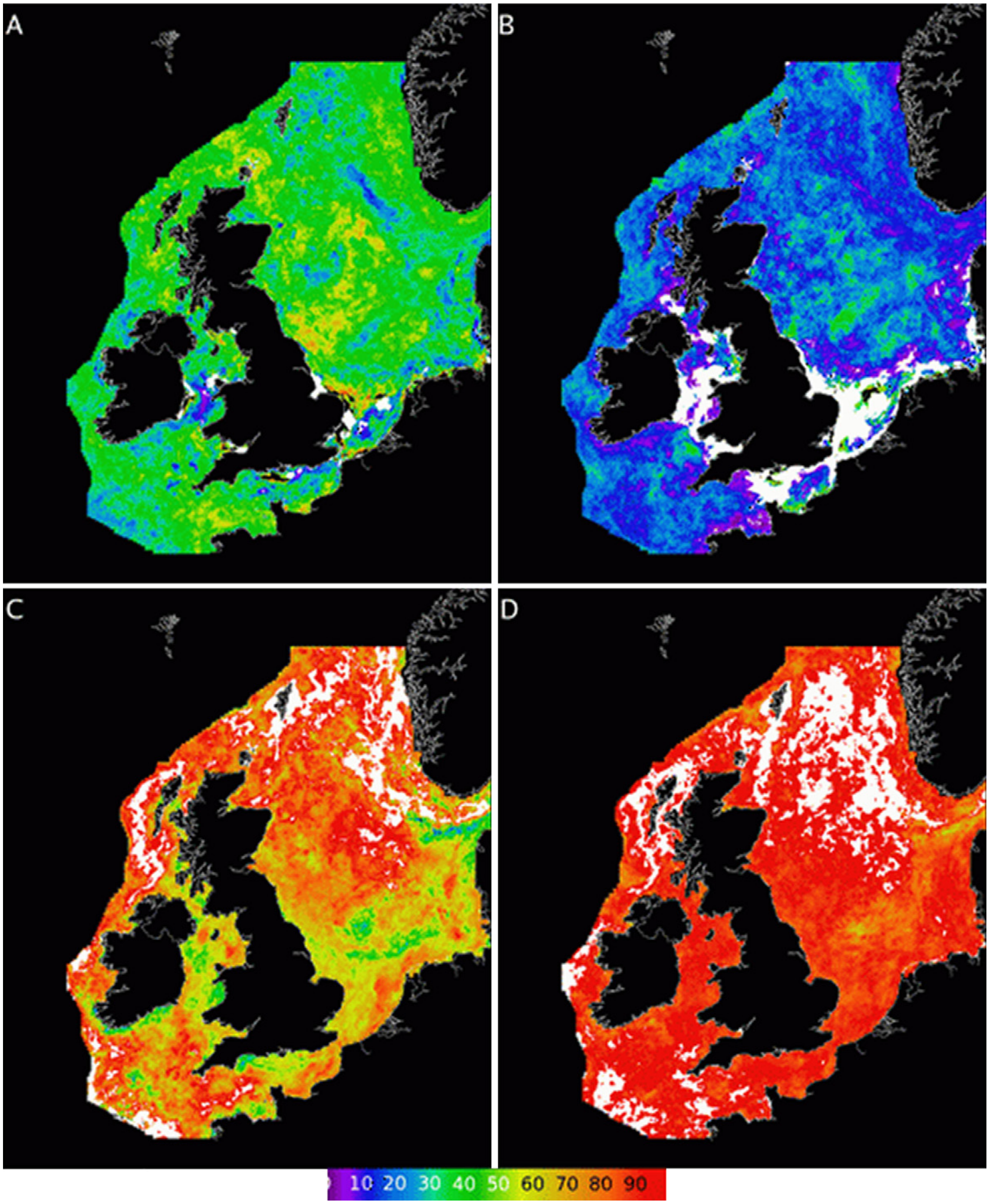

Fig. 4. PPV and NPV estimator fields (units are %). (A) PPV for threshold > mean chlorophyll concentration for that pixel, (B) PPV for threshold > 1.5 mean chlorophyll concentration for that pixel, (C) NPV for threshold > mean chlorophyll concentration for that pixel, (D) NPV for threshold > 1.5 mean chlorophyll concentration for that pixel. The data used as input were the weekly composite chlorophyll fields of both MRCS and Aqua (generated from the daily passes) for 2004 and 2005. Black indicates zero probability, White indicates no data; a pixel where the model bias is such it never exceeds the threshold (PPV maps) for falls below it (NPV maps).

is much higher (>70%) mostly either in the middle of stratified regions or in near shore regions. The regions of very low skill (<20%) occur in the turbid well-mixed waters (however see discussion for caveats concerning the satellite data) and in frontal regions particularly along the boundary of the Norwegian coastal current. When the threshold for a bloom is raised to 50% above the mean chlorophyll concentration the model skill is much lower (Fig. 4b); PPV < 30% for most of the domain, with the lowest values occurring in frontal regions. In the eutrophic regions the model is biased towards underestimation. Consequently there are substantial areas where the model does not predict values above the threshold and has no skill (indicated in white). The corresponding skill maps for negative events are shown in Fig. 4c and d. At the lower threshold the model gets 90% of non-bloom events correct in the stratified regions and the skill is much lower in the (<70%) in the eutrophic regions. At the higher threshold the model correctly predicts no bloom occurrence over 90% of the time. In both cases over estimation of chlorophyll concentration in the Northern and Western parts of the domain indicates that the model never predicts values below the threshold.

4. Discussion and conclusions

It is apparent that the model has some aspect of skill for predicting blooms at the mean, but not at the higher (>50% mean) threshold. Also if the model indicates no bloom it is usually correct. However it is also apparent that there are many discrepancies between the model and satellite data, the most notable being, errors in the timing of the spring bloom (e.g. Fig. 3; Lewis et al., 2006) and high bias in frontal regions (Fig. 1; Siddorn et al., 2007). The discrepancies in the timing of the spring bloom can be attributable to under estimation of turbulent mixing in the stratified regions and poor model representation of the in-water optics in the well-mixed regions. Further evidence and the potential mechanisms are discussed in more detail in Holt et al. (2005), Allen et al. (2007a,b), and Lewis et al. (2006). The errors associated with physical structures (fronts) are attributed to enhanced mixing in these regions (Siddorn et al., 2007).

Discrimination analysis allows us to assess model performance in a way which is potentially highly relevant for environmental management. Many decisions are based on thresholds. For example OSPAR criteria for enhanced eutrophic status, has a series of assessment criteria (e.g. winter dissolved nitrate or phosphate concentrations, increased winter N:P ratio and elevated maximum and mean chlorophyll concentrations). Elevated levels are defined as 50% above the regional specific background concentration. Once these thresholds are defined we can use the discrimination analysis to determine the probability that a predicted elevated level in the model is correct.

A basic assumption of the method outlined in this paper is that the satellite data represents the 'truth'. Inevitably our ability to interpret this information is limited by the quality of the satellite chlorophyll estimates used. The highly eutrophic regions where high biomass blooms occur are optically complex (classified as case II), being characterised by high sediment loads and both land derived and marine dissolved coloured organic matter (Prieur and Sathyendranath, 1981). Such waters present a major challenge to satellite algorithms (Doerffer and Fischer, 1994; Ruddick et al., 2001) and the current operational band ratio algorithms are unable to accurately retrieve chlorophyll concentrations (Blondeau-Patissier et al., 2004; Harding et al., 2005) in case II waters. It is imperative that there is a significant improvement in accuracy of chlorophyll estimates from satellite in case II regions so we can better assess model predictive skill. A possible pragmatic solution to this problem, with relevance to our particular application, is to introduce a statistical data error model with appropriately higher variance in case II waters. This would result in a map of "correct classification probability" relevant throughout the domain. However it is likely that even if a "perfect" chlorophyll product from space were developed in case II waters, this problem is only a second order effect when compared with the complexity of developing models to forecast/nowcast/hindcast the occurrence and magnitude of algal blooms and their possible toxicity.

In the more oceanic waters where the variable optical signature is dominated by phytoplankton (classified as case I waters) the accepted accuracy goal from satellite is chlorophyll to within 30%.

An important aspect of modelled data is that it allows an expert user to infer from it aspects of the system that the model is not able to simulate directly. In the same way that a weather forecaster takes information about pressure and moisture fields from a numerical weather prediction model to infer what the weather will be, a marine environmental forecaster may be able to take information from a numerical ecosystem prediction model to predict aspects of the ecosystem not directly simulated. For example, we know that HAB events often coincide with distorted nitrate: phosphate ratios (e.g. Burkholder et al., 2001; Radach et al., 1990) and low turbulence (e.g. Dahl and Tangen, 1993), and that toxin production often occurs when the phytoplankton is nutrient stressed (e.g. Johansson and Graneli, 1999; Anderson et al., 1990). Currently we cannot make species-specific forecasts of HABs but we can simulate the aforementioned indicators. If suitably large data sets are available, we can assign thresholds for these indicators and determine the probability the model predicts an event correctly in much the same way as we have outlined here for satellite data. Therefore in principle, we can combine information from hydrodynamic and ecosystem models to provide probability-based risk maps of HAB occurrence in a manner similar to that suggested by Brown et al. (2002) and Decker et al. (2007).

Acknowledgements

This work was partly funded by the EC MERSEA Integrated Project (Co No AIP3-CT-2003-502885) and the Plymouth Marine Laboratory NERC core strategic science program. Satellite data was acquired automatically from the NASA OceanColor Web (http://oceancolor.gsfc.nasa.gov); processed and mapped by the NERC Earth Observation Data Acquisition and Analysis Service (NEO-DAAS) at the Plymouth Marine Laboratory. This work forms part of the UK National Centre for Ocean Forecasting (NCOF).[SS]

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