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Cyanobacterial blooms in the Baltic Sea: Correlations with environmental factors

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ABSTRACT

Massive cyanobacteria blooms occur almost every summer in the Baltic Sea but the capability to quantitatively predict their extent and intensity is poorly developed. Here we analyse statistical relationships between multi-decadal satellite-derived time series of the frequency of cyanobacteria surface accumulations (FCA) in the central Baltic Sea Proper and a suite of environmental variables. Over the decadal scale (~5-20 years) FCA was highly correlated ($R^2 \sim 0.69$) with a set of biogeochemical variables related to the amount of phosphorus and hypoxia in bottom layers. Water temperature in the surface layer was also positively correlated with FCA at the decadal scale. In contrast, the inter-annual variations in FCA had no correlation with the biogeochemical variables. Instead, significant correlations were found with the solar shortwave direct flux in July and the sea-surface temperature, also in July. It thus appears that it is not possible to predict inter-annual fluctuations in cyanobacteria blooms from water chemistry. Moreover, environmental variables could only explain about 45% of the inter-annual variability in FCA, probably because year-to-year variations in FCA are significantly influenced by biological interactions.

1. Introduction

Nitrogen-fixing cyanobacteria have been an important component of the Baltic Sea ecosystem for millennia (Bianchi et al., 2000; Funkey et al., 2014) and contribute substantially to ecosystem productivity when inorganic nitrogen is in short supply (Larsson et al., 2001; Karlson et al., 2015). As many cyanobacteria are toxic and form harmful algal blooms, there has been a lot of effort to identify environmental factors that favour such blooms. Numerous publications (Niemi, 1979; Kahru et al., 1994; Wasmund, 1997; Paerl and Huisman, 2008, 2009; Paerl et al., 2011) have pointed out environmental conditions that enhance the competitive advantage and growth of cyanobacteria such as high inorganic phosphorus to nitrogen ratio, high water temperature, high solar irradiance and low winds. However, these conditions are not sufficient to quantitatively predict the concentration and the extent of cyanobacterial blooms. As a first step towards such predictions, we here analyse statistical relationships between a unique multi-decadal satellite-detected time series of near-surface cyanobacteria concentrations in the Baltic Sea (Kahru and Elmgren, 2014, extended to 2018) and various environmental variables.

The spatial patterns of cyanobacteria accumulations are extremely patchy with the characteristic multi-scale stripes and swirls (e.g. Kahru et al., 1994; Kutser, 2004) that makes their sampling with conventional water samplers highly unreliable. We used a satellite-derived time series of over three decades that is made possible by the tendency by one of the co-dominant cyanobacteria species in the open Baltic Sea, *Nodularia spumigena*, to form dense surface accumulations. The other co-dominant species, *Aphanizomenon* sp., is typically distributed deeper in the water column (Hajdu et al., 2007; Rolff et al., 2007) and therefore not specifically detected in this time series. Since *Aphanizomenon* in the Baltic Sea is non-toxic and contributes little to the surface blooms, the blooms registered by satellites provide valid measurements of the frequency and extent of cyanobacterial blooms of main societal concern. The satellite data used here are based on a pixel size of ~1 km^2, which is above the scale of typical stripes and swirls seen from ships. However, the sub-pixel structures are integrated into the pixel values that are well correlated with higher resolution measurements, e.g. from continuous in-water measurements along ship tracks (Kahru and Elmgren, 2014).

While statistical relationships do not prove causation, they provide

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clues to finding the environmental conditions that regulate cyanobacterial blooms in the Baltic Sea, and could help in modelling efforts to predict the likelihood of extensive blooms in the future. We use a statistical method called partial least squares (PLS) regression, a technique that combines the features of principal component analysis and multiple linear regression (CenterSpace, 2016). In the terminology of PLS we try to predict one or more variables from combinations of a set of variables, some of which may be highly correlated. Whereas the principal components regression computes the factor scores using the covariance structure between predictor variables, PLS regression computes factor scores from the covariance structure between the predictor and the response variables. The term prediction is used here not as a forecast into the future but as a way to statistically fit the measured time series with a modelled time series using a suite of input variables.

2. Methods

2.1. Frequency of Cyanobacteria accumulations (FCA)

To characterize the frequency and extent of cyanobacteria blooms we have developed an index (Kahru et al., 2007; Kahru and Elmgren, 2014) called the frequency of cyanobacteria accumulations (FCA). FCA is the ratio of the number of days when cyanobacteria accumulations were detected to the number of days with unobstructed (cloud-free) satellite views of the sea surface, calculated for each pixel, and is not directly dependent on the number of available images. As satellite detection of cyanobacteria accumulations is limited to periods of clear skies and availability of near-noon satellite overpasses, FCA normalizes the number of detections to the number of observations. Even though normalized, FCA values are less reliable if the number of available images is small. As most environmental datasets used here (see below) start in 1987, we use FCA time series from 1987 to 2018.

Cyanobacteria blooms in the Baltic Sea often start already in June but the bulk of the accumulations occurs during the months of July and August. We therefore use FCA calculated over the 2-month period of July-August as the annual estimate of the strength of the blooms.

In past publications (Kahru et al., 2007; Kahru and Elmgren, 2014), we used FCA calculated over an area that covered most of the Baltic Sea including the gulfs of Bothnia, Finland and Riga. As near-coast turbidity and resuspended sediments in shallow areas can interfere with our method of cyanobacteria detection, we restrict our analysis here to the central Baltic Proper deeper than 15 m (Fig. 1). In other aspects the FCA time series follows the methods of Kahru and Elmgren (2014) and was extended to 2018 by using satellite data from MODIS-Aqua, MODIS-Terra, VIIRS-SNPP and VIIRS-JPSS1 satellite sensors (Fig. 2).

Visual inspection of the FCA time series showed variations at multiple scales which may have different associations with relevant environmental variables, as discussed in Kahru et al. (2018). We therefore separated the time series into the longer term (called decadal) and the year-to-year or inter-annual changes. The low-frequency part of the time series (FCA_{dec}) was created by using a 3-year running mean on FCA. The respective high-frequency part (FCA_{inter}) was created by subtracting the 3-year running mean, i.e. $FCA_{inter} = FCA - FCA_{dec}$. The numerical values of the time series of FCA and its components are provided in the Supplement.

2.2. Environmental variables

A total of 35 time series of various environmental variables (Table 1) were compiled from both satellite-derived and in situ datasets for evaluation for relationships with estimates of cyanobacteria abundance. Details on those variables are given in the Supplement.

2.2.1. Partial least squares (PLS) regressions

Statistical relationships between time-series of FCA and 35 environmental variables (Table 1) were evaluated using PLS regressions as implemented in the NMath numerical libraries (http://www.centerspace.net/nmath). The analysis was started with correlations between FCA and each of the environmental variables. Combinations of an increasing number of variables were then used in PLS and the combination with the highest coefficient of determination (R^2) and the lowest root mean square error of prediction (RMSEP) were determined. The number of variables in a combination was increased (up to four) until no significant improvement was achieved by adding more input variables.

3. Results

At the decadal time scale, i.e. after smoothing with the 3-year running mean filter, the FCA time series is most strongly correlated with a group of biogeochemical variables (Fig. 3). In particular, variables related to basin-scale phosphorus availability such as DIP, P_excess, HA and N/P (see Table 1 for definitions) have the highest correlations ($0.42 < R^2 < 0.60$). The next group in the influence hierarchy on decadal scale variations in FCA is a group of *in situ* (0 − 15 m) water temperature variables (e.g. TNBP_0702-0904) with correlations exceeding the correlations with satellite-derived sea-surface temperatures. Correlations with in-water temperatures are strongest with water temperature in the Northern Baltic Proper and with water temperature at station BY15 in Eastern Gotland basin, and weaker with the water temperature averaged over the whole Baltic Proper. Variables related to solar irradiance (SDU, SID, SIS), wind speed components and phosphate concentrations in the surface layer in summer have correlation below the 95% significance at the decadal time scale.

Correlations with the inter-annual component of FCA time series, i.e. after subtracting the smoothed time series, are very different from those with the low-frequency component of FCA (Fig. 3). In general, correlations are lower than the correlations with biogeochemical variables at the decadal scale and are statistically significant only for a few variables. The strongest correlations at the inter-annual time scale are with the direct solar shortwave flux in July (two closely related variables SidAnomJul and SIDmmJul), followed by satellite-derived sea-surface temperature (SST), also in July (SSTjul). Correlations between FCA_{inter} and wind components are low (near 90 % significance level) and correlations with biogeochemical variables are all practically zero.

Table 2 lists the environmental variables and combinations of variables that have the highest R^2 and lowest RMSEP for both FCA_{dec} and FCA_{inter}. As environmental variables within groups are highly correlated, the next most significant variable in a combination of variables is typically from another group. It appears that the first variable provides most of the predictive power and the effect of adding additional variables is quite limited. This is particularly true for FCA_{dec} for which R^2 increased only from 0.60 to 0.69 when increasing the number of predictor variables from one to four. For FCA_{inter} the effect of adding variables was stronger, with R^2 increased from 0.31 to 0.45 from one variable to a combination of four variables. While the strongest correlations with individual variables at the decadal time scale are all with the biogeochemical variables (DIP, P_excess, HA and N/P), those variables are all closely correlated with each other and therefore only DIP is present in the best multi-variable combinations (Table 2). DIP alone explains 60 % of FCA_{dec}. The sets of variables with the highest correlations are completely different at the decadal and at the inter-annual time scales. While the in situ water temperature variables in Northern Baltic Proper (e.g. TNBP_0702-0904)) are significantly correlated with FCA_{dec}, they don't show up in the two-variable combinations with the highest R^2. For FCA_{inter} the second most important variable in a combination is the July sea-surface temperature (SSTjul). The best multi-variable combinations for predicting FCA_{dec} include also anomalies of the direct shortwave solar flux in August and May (SidAnomAug and SidAnomMay) but their effect is small. The respective best multi-variable combination for predicting FCA_{inter} includes (in that order) the anomaly of direct solar flux in July (SidAnomJul), SST in

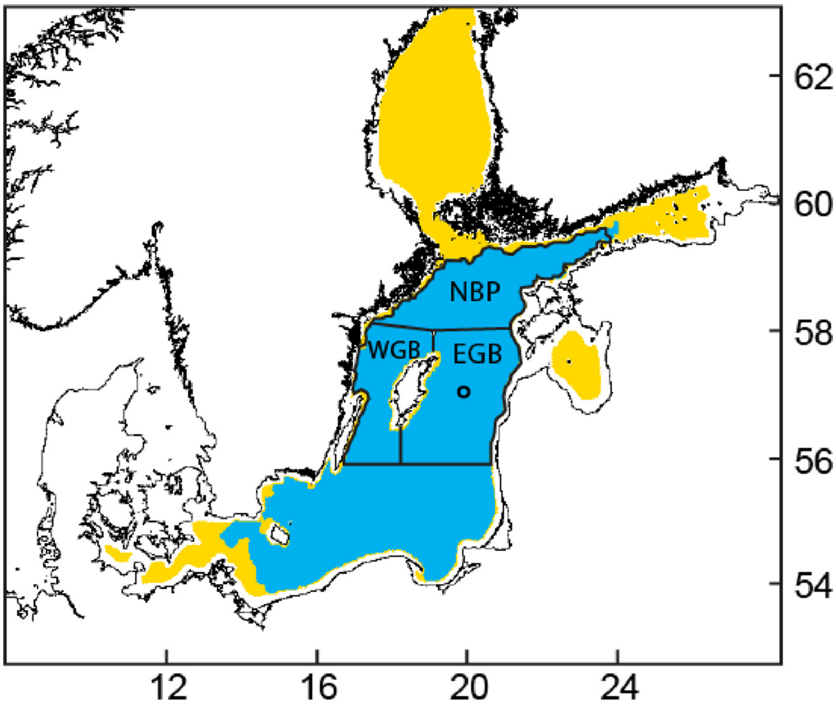

Fig. 1. Map of the study area. Central Baltic Proper (CBP, blue area) is the area excluding shallow coastal areas (< 15 m) and the gulfs. The sub-basins of Northern Baltic Proper (NBP), Western Gotland basin (WGB) and Eastern Gotland Basin (EGB) are shown. The small circle shows the location of the Baltic monitoring station BY15. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

July, the surface layer phosphate concentration in June-July (PO4_15m_0609-0709) and the sum of temperatures with SST over 17 °C. No variable from the in situ temperature variable group or from the basin-scale biogeochemical group is included in the best combinations for predicting FCA_{inter}. However, even the best 4-variable combination explains only 45 % of the variance of FCA_{inter} compared to 69 % of the variance in FCA_{dec} (Table 2, Fig. 4). Surprisingly, the correlations of sunshine duration averaged over July and August (SDUjul-aug) and those of the wind components are not significant ($p = 0.05$) when evaluated individually against FCA_{inter} and are not in the best multi-variable combination for predicting FCA_{inter} (Fig. 2 and Table 2). Phosphate concentrations in the surface layer in summer have no significant correlations with either FCA_{dec} or FCA_{inter} when taken individually but PO4_0-15m_0609-0709 is included in the best 3- and 4-variable combinations predicting FCA_{inter}.

4. Discussion and conclusions

Our analysis of the FCA time series in the central Baltic Proper (Fig. 2) showed that the environmental variables with significant correlations with FCA were almost completely different for the decadal scale and for the inter-annual scale variability in FCA. On the decadal scale, the highest correlations were clearly with basin-scale biogeochemical variables related to pools of phosphorus and the extent of hypoxic areas. Increase of hypoxia in the Baltic Sea has been linked to increased inputs of nutrients from land (Carstensen et al., 2014). Hypoxia in bottom waters is also affected by the inflows of high-salinity North Sea waters that trigger changes in the whole water column and may lead to surface cyanobacteria blooms (Kahru et al., 2000). While the linkage between decadal scale changes in FCA and the selected biogeochemical variables makes sense as phosphorus and not nitrogen is the main limiting nutrient for N_2-fixing cyanobacteria, correlations do not mean causation and these correlations may be caused by similar long-term dynamics due to different reasons. However, these positive correlations support the “vicious circle” hypothesis coupling cyanobacteria blooms to anoxic conditions (Vahtera et al., 2007; Funkey et al., 2014; Savchuk, 2018). Therefore, quantitative estimation of the intensity of cyanobacteria blooms in the coming summer based on monitoring and/or modelling of the bottom water anoxic conditions during the previous winter (Janssen et al., 2004; Vahtera et al., 2007) seemed to be a promising lead towards quantitative prediction of the Baltic Sea environment. However, our results show that at the inter-annual scale, the biogeochemical variables have no influence on the variations of FCA and that makes this prospect rather dubious. Either we can hypothesize that the accuracy of the annual estimates of these biogeochemical variables is not sufficient (i.e. the inter-annual

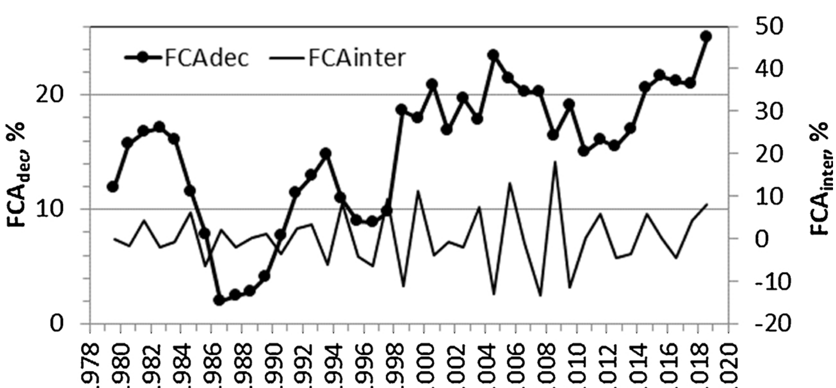

Fig. 2. Time series (1979–2018) of the 2 components of the frequency of cyanobacteria accumulations: the low-frequency (decadal) part FCA_{dec} (black filled circles, thick line, left axis) and the high-frequency (interannual) part FCA_{inter} (thin line, right axis) averaged over the Central Baltic Proper (blue area in Fig. 1). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 1
Environmental variables used in PLS to predict the low-frquency component FCA_{dec} and the inter-annual component FCA_{inter}. R^2 values that are significant at $p < 0.01$ are in bold.

Variable	Explanation	R^2 with FCA_{dec}	R^2 with FCA_{inter}
SSTjun	Average satellite SST for June	0.19	0.01
SSTjul	Average satellite SST for July	0.07	**0.28**
SSTaug	Average satellite SST for August	0.18	0.04
SSTjul-aug	Average satellite SST for July-August	0.15	0.19
DaysAbove14	Number of days with SST above 14 °C	0.17	0.07
SumAbove14	Sum of daily SSTs above 14 °C	0.15	0.17
DaysAbove17	Number of days with SST above 17 °C	0.11	0.15
SumAbove17	Sum of daily SSTs above 17 °C	0.12	0.12
TBY15_Annual	In situ annual mean temperature for 0 – 15 m at BY-15	**0.30**	0.01
TBY15_0525-0908	Mean temperature for 0 – 15 m for Jun 24 - Sep 8 at BY-15	**0.24**	0.06
TBY15_0709-0824	Mean temperature for 0 – 15 m for Jul 9 - Aug 24 at BY-15	**0.27**	0.17
TNBP_Annual	In situ annual mean temperature for NBP	**0.29**	0.01
TNBP_0531-0904	In situ mean temperature for May 31 - Sep 4 for NBP	**0.33**	0.03
TNBP_0702-0904	In situ mean temperature for Jul 2 - Sep 4 for NBP	**0.20**	0.03
TBP_Annual	In situ annual mean temperature for Baltic Proper	**0.21**	0.02
TBP_0531-0904	In situ mean temperature for May 31 - Sep 4 for Baltic Proper	**0.22**	0.06
TBP_0702-0904	In situ mean temperature for Jul 2 - Sep 4 for Baltic Proper	0.17	0.10
SDUjul-aug	Sunshine duration averaged for July-August	0.01	0.09
SIDmmJul	Shortwave direct irradiance averaged for July	0.00	**0.31**
SIDmmJulAug	Shortwave direct irradiance averaged for July-August	0.00	0.14
SidAnomMay	Shortwave direct irradiance anomaly for May	0.08	0.02
SidAnomJun	Shortwave direct irradiance anomaly for June	0.09	0.09
SidAnomJul	Shortwave direct irradiance anomaly for July	0.00	**0.31**
SidAnomAug	Shortwave direct irradiance anomaly for August	0.01	0.01
SidAnomJulAver3	Shortwave direct irradiance 3 month running mean for July	0.04	**0.22**
SISmmJulAug	Shortwave irradiance averaged for July-August	0.00	0.12
uSeaWindsJulAug	Average eastward wind for July-August (m s^{-1})	0.00	0.07
vSeaWindsJulAug	Average northward wind for July-August (m s^{-1})	0.03	0.09
HA	Hypoxic area, km^2	**0.53**	0.00
DIN	Dissolved inorganic nitrogen in Kt	0.19	0.01
DIP	Dissolved inorganic phosphorus in Kt	**0.60**	0.01
N/P	Ratio DIN/DIP	**0.42**	0.00
P_excess	Phosphorus excess in Kt	**0.55**	0.00
PO4_0525-0609	Phosphate concentration 0 – 15 m, May 25- June 9 at BY-15	0.00	0.00
PO4_0609-0709	Phosphate concentration 0 – 15 m, June 9-July 9 at BY-15	0.00	0.00

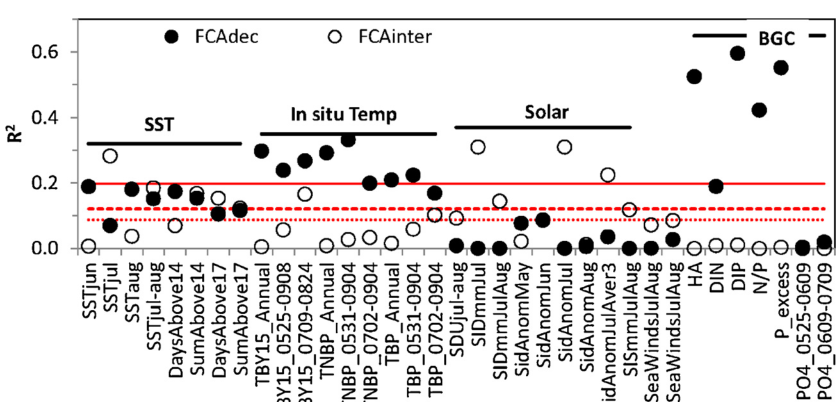

Fig. 3. Influence of various environmental variables (coefficient of determination, R^2) on the low-frequency („decadal“) part of FCA (FCA_{dec}, filled circles) and and the high-frequency („interannual“) part (FCA_{inter}, open circles) for Central Baltic Proper. The 90 % (red dotted line), 95 % (red dashed line) and 99 % (red solid line) confidence thresholds are shown. Variables are grouped into satellite SST, In situ temperature, Solar, and biogeochemical (BGC). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

variations of these biogeochemical variables are mainly "noise") or that they truly do not matter once certain levels are reached.

Correlations with the year-to-year fluctuations are more likely to reveal causal relationships as they are less likely to be caused by coincidental changes. However, they too are affected by random fluctuations and measurement errors in all variables. It makes sense that at the inter-annual scale (i.e. shorter scale) the variables with the highest correlations are the monthly shortwave solar flux in July and SST in July. It appears also that July is the critical month and the correlations with a number of variables in the months of May, June and August are much lower than those for July because the growth maximum occurs before the biomass peak as described by Wasmund et al. (2005). On the other hand, it is also clear that as the decadal scale changes in solar flux are minor compared to the respective changes in other variables, the solar variables cannot be expected to be the primary variables affecting FCA at the decadal scale.

While the decadal scale changes in FCA are positively related to both in-water temperatures and satellite-detected SST, correlations with in-water temperatures are higher. This can be explained by the satellite-derived SST being affected by surface microlayer effects, making it less representative of the bulk water temperature that matters most to the cyanobacteria, even though satellite SST has superior coverage and sampling frequency. The in-water temperature at station BY15 has a particularly strong effect on indices of cyanobacteria blooms, probably due to its relatively high temporal sampling frequency. Satellite SST estimates can be affected by the surface microlayer effects at low-wind conditions in the summer (the so-called "hot spots") and near-surface blooms may actually enhance the surface water temperature (Kahru

Table 2
PLS predictions of FCA low-frequency (FCA_{dec}) and inter-annual (FCA_{inter}) components for the Central Baltic Proper (CBP), 1987-2018. N is the number of variables included in the prediction, R^2 is the coefficient of determination and RMSEP is the root mean square error of prediction.

Predicted variable	N	Input variables	R^2	RMSEP
FCA_{dec} for Central Baltic Proper	1	DIP	0.60	0.151
	2	DIP, SidAnomMay	0.62	0.146
	3	DIP, SidAnomMay, SidAnomAug	0.66	0.139
	4	DIP, SidAnomMay, SidAnomAug, TNBP_0702-0904	0.69	0.132
FCA_{inter} for Central Baltic Proper	1	SidAnomJul	0.31	0.194
	2	SidAnomJul, SSTjul	0.39	0.182
	3	SidAnomJul, SSTjul, PO4_0-15m_0609-0709	0.43	0.177
	4	SidAnomJul, SSTjul, PO4_0-15m_0609-0709, SumAbove17	0.45	0.173

et al., 1993). The correlations of both FCA_{dec} and FCA_{inter} with satellite-detected eastward and northward wind components are not significant which suggests that temporal integration of these highly variable measurements into monthly mean values may not be meaningful. It is a common perception that surface accumulations of cyanobacteria are dissipated by wind action. However, our algorithm for detecting cyanobacterial accumulations reflects not only the surface floating scum but also the backscatter from the near-surface layer just below, reducing the effect of winds on FCA.

In the northern Baltic Proper (areas NBP, WGB, EGB in Fig. 1), the year-to-year fluctuations of FCA have a quasi-regular oscillation with a period of ~3 years (Kahru et al., 2018). This seems like an internal oscillation of unknown origin and the causal links of the oscillation to environmental variables are not known. The oscillations reduce the correlations between FCA and the environmental variables included in this study. The oscillations are most evident in the northern Baltic Proper where none of the environmental variables had a R^2 significant at $p < 0.05$ level with year-to-year fluctuations in FCA (Kahru et al., 2018). When the whole central Baltic is considered, the effect of the oscillations is reduced and significant correlations are found with some environmental variables (e.g. direct solar flux and SST in July). However, because of the variance introduced by the unexplained oscillations, environmental variables can explain only ~45 % of the total variations of FCA at inter-annual scale. The remaining ~55 % is the unexplained variance due to the internal oscillation and random errors. Comparison of FCA estimates using different satellite sensors (Kahru and Elmgren, 2014) shows that the measurement error in 2-month FCA estimates is relatively low, less than 5 %. This suggests that about half of the inter-annual variations in FCA in the central Baltic Sea cannot be estimated from environmental conditions and is probably due to biological interactions.

We hope that this work will help to improve current models of cyanobacteria dynamics (e.g. Hense, 2007) and to provide better hindcasts of the FCA time series using measured and modelled environmental variables. According to our results, in order to predict the inter-annual changes in FCA the forward models would need to predict the weather variables in July which is not going to be easy.

Declaration of Competing Interest

None

Acknowledgements

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.hal.2019.101739.

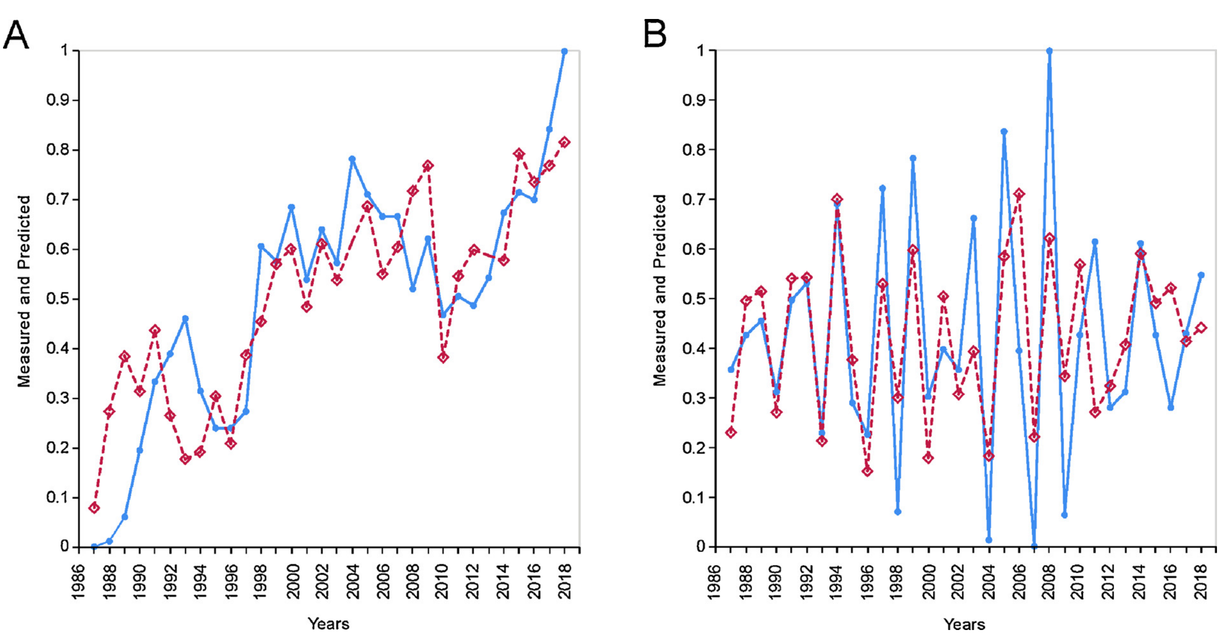

Fig. 4. Predicting the frequency of cyanobacteria accumulations (FCA) in the central Baltic Sea from time series of environmental variables with partial least squares (PLS) regression. The time series have been normalized to a range [0, 1], the observed series is shown with a blue line and the predicted series with a red dashed line with open diamonds. A, FCA low-frequency component (FCA_{dec}) predicted from DIP, SidAnomMay, SidAnomAug, TNBP_0702-0904 ($R^2 = 0.69$); B, FCA inter-annual component (FCA_{inter}) predicted from SidAnomJul, SSTjul, PO4_0-15m_0609-0709, SumAbove17 ($R^2 = 0.45$). The variable names are listed in Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

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