

Synoptic scale analysis of mechanisms driving surface chlorophyll dynamics in the North Atlantic

Ana Sofia de Araújo Ferreira¹, Hjálmar Hátún², François Counillon³, Mark R Payne¹, and André W Visser¹

¹Centre for Ocean Life, National Institute of Aquatic Resources, Technical University of Denmark, Denmark

²Faroe Marine Research Institute, Nóatún 1, P.O. Box 3051, FO 110 Tórshavn, Faroe Islands

³Nansen Environmental and Remote Sensing Center, Thormøhlensgate 47, Bergen, Norway

Correspondence to: Ana Sofia de Araújo Ferreira (asofiaferreira@gmail.com)

Abstract. Several hypotheses have been proposed for the onset of the spring phytoplankton bloom in the North Atlantic. Our main objective is to examine which bottom-up processes can best predict the annual increase in surface phytoplankton concentration in the North Atlantic by applying novel phenology algorithms to ocean colour data. We construct indicator fields and time series which, in 5 various combinations, provide models consistent with the principle dynamics previously proposed. Using a multimodel inference approach, we investigate the evidence supporting these models, and how it varies in space. We show that, in terms of bottom-up processes alone, there is a dominant physical mechanism, namely mixed layer shoaling, that best predicts the interannual variation in the initial increase in surface chlorophyll across large sectors of the North Atlantic. We further show 10 that different regions are governed by different physical phenomena, and that wind-driven mixing is a common component with either heat flux or light as triggers. We believe these findings to be relevant to the ongoing discussion on North Atlantic bloom onset.

1 Introduction

About half of global primary production is performed by marine phytoplankton. Phytoplankton production fuels marine ecosystems and the harvesting of marine living resources, as well as playing an important role in global carbon cycling (Field et al., 1998). In many parts of the world's oceans, marine primary production undergoes a distinct seasonal cycle, with the major part of production occurring in the spring bloom (Longhurst, 1995; Martinez et al., 2011; Platt et al., 2010). This seasonal cycle is particularly apparent in the North Atlantic (Yoder et al., 1993), where it imprints seasonal 20 variations in species abundance and annual routines (*e.g.* spawning, migration) throughout the ma-

rine food web from zooplankton (Gaard, 2000; Gislason and Silva, 2012; Heath et al., 2000), to fish (Trenkel et al., 2014; Badcock and Merrett, 1976) and marine mammals (Pauly et al., 1998). In the North Atlantic, the progression of primary production throughout the year, and its variation between years, is commonly used as a proxy for ecosystem state (Townsend et al., 1994; Frajka-Williams and 25 Rhines, 2010; Lévy et al., 2005). The North Atlantic spring bloom is an important biological event and has attracted considerable attention during the last decades (Behrenfeld, 2010; Chiswell et al., 2013; Platt et al., 2003).

Phenology is the term used to describe the study of the timing of annual recurring biological events, such as the observed “greening” of the surface ocean, an indicator of bloom initiation. Phe- 30 nology provides a staple for understanding the cascading fluctuations throughout the food web. To achieve this, a good phenology metric should be accurate, precise, and sensitive to the underlying environmental processes, both physical or biological (Ferreira et al., 2014). Much of the recent interest in spring bloom dynamics (Behrenfeld, 2010; Chiswell et al., 2013) concerns the mechanisms that influence different characteristics of the annual cycle.

35 Chlorophyll concentration is, arguably, the most important ecological variable setting the pace of life in temperate and high latitude seas. In this study, we use surface chlorophyll concentrations as derived from satellite ocean colour to detect spring bloom initiation (Cole et al., 2012; Sasaoka et al., 2011; Brody et al., 2013). We thus assume that the chlorophyll concentration at the surface represents that of the surface mixed layer (Evans and Parslow, 1985). While we note that some 40 aspects of bloom dynamics are more properly described by integrating phytoplankton biomass over the mixed layer (Behrenfeld, 2010), it is the surface chlorophyll that is the most readily accessible via the highly-resolved (both spatially and temporally) ocean colour products.

There are essentially three environmental processes that can change the surface chlorophyll concentration: phytoplankton growth through light and nutrients; loss terms, such as respiration, grazing, 45 coagulation and sinking; and dilution through mixed layer deepening. These processes are particularly important during two key phases of the seasonal cycle: 1) events that lead to an increase in phytoplankton biomass - bloom initiation; and 2) conditions that halt the net increase in biomass - the peak of the bloom. Phytoplankton biomass will increase whenever the growth rate exceeds the loss rate (Sverdrup, 1953). This picture, with regards the distinction between biomass and surface 50 chlorophyll concentration, is somewhat complicated by dilution; a deepening mixed layer dilutes the concentration but has no effect on the biomass, a process that has repercussion on the feeding success and thus population dynamics of grazers. However, a shoaling mixed layer has no direct influence on the concentration but removes biomass to some extent. These processes and their implications for phytoplankton, the resources they rely on, and their grazers, have been carefully considered in recent 55 re-analyses of spring bloom dynamics (Behrenfeld et al., 2013a; Lindemann and St John, 2014).

It is also fair to say that the annual trajectory of phytoplankton biomass and surface phytoplankton concentration follow different dynamics (Chiswell et al., 2013). While we recognise that phy-

toplankton biomass variation is an important aspect of spring bloom dynamics, in this paper, we examine which fundamental physical processes may best predict the timing of the increase in surface phytoplankton concentrations. Furthermore we do so since ocean surface colour is a readily available synoptic scale observable spanning many years of measurements. The interannual variability in bloom timing is evaluated in terms of how much the increase in surface layer chlorophyll is advanced or delayed compared to the day of climatological maximum rate of increase.

1.1 Mixed layer shoaling

Over the years, several theories have been put forwarded which, in one way or the other, try to model the growth and loss rates in terms of fundamental processes (Table 1 and Figure 1). The classic application of the growth-loss view of bloom initiation relates to when photosynthetic production of organic matter surpasses respiration (Sverdrup, 1953), where respiration refers to all losses and is constant. This hypothesis is commonly referred to as the “critical depth hypothesis”, which states that a bloom begins when the surface mixed layer shoals to a depth above the critical depth (where integrated production equals losses). The shoaling of the mixed layer means that individual phytoplankton cells remain longer in the euphotic zone (Siegel et al., 2002; Sverdrup, 1953; Chiswell, 2011). By extension, this suggests that the light intensity integrated over the mixed layer is the most relevant factor driving phytoplankton blooms in the North Atlantic. Here, we term this hypothesis the “critical depth model” (Table 1).

1.2 Active mixing

Mixed layer shoaling, however, is not the only process which can increase the residence time of primary producers in the well-lit surface ocean. Similar effects can be driven by periods of low surface mixing (Townsend et al., 1992). This has led to a series of alternative interpretations, which highlight active mixing (specifically the lack thereof) as a key ingredient (Townsend et al., 1994; Huisman et al., 1999; Taylor and Ferrari, 2011a).

One of the first quantitative studies (Townsend et al., 1994) examined the combined effects of wind-driven mixing and light: the hypothesis being that blooms can occur during periods when light is low but increasing and turbulent mixing weakens. These conditions can be met well before the surface mixed layer begins to shoal. We call this the “critical light exposure model” (Table 1).

This type of reasoning can also lead to only considering the competing effects of stratification by solar heating, and destratification by wind-driven mixing. This view encapsulates the key elements of the “critical turbulence model” (Huisman et al., 1999, 2002), where brief interludes in mixing and heating produce a stable layer in which phytoplankton cells are retained within the euphotic layer. Thus, a balance between heat-flux and wind-driven mixing may explain North Atlantic phytoplankton seasonality (Table 1).

More recently, Taylor and Ferrari (2011b) have shown that blooms may be detected much earlier than the shoaling of the mixed layer depth, and it has been proposed that blooms can be initiated as soon as deep convection ceases (Taylor and Ferrari, 2011a). That is, as soon as the ocean experiences
95 a net inward heat flux. In this context, the timing of the transition from net cooling to net warming is a key element linked to the variability of phytoplankton seasonality. We term this the “critical heat flux model” (Table 1).

1.3 Other processes not considered

There have been theories also focusing on specific regional effects. For instance, Mahadevan et al.
100 (2012) were able to link bloom onset to eddy-driven stratification, prior to net warming. Fronts were also found to trigger high-latitude blooms by reduced mixing, which explains high chlorophyll levels in light-limited regions (Taylor and Ferrari, 2011b). Other studies (Frajka-Williams and Rhines, 2010; McGillicuddy et al., 2007; Garçon et al., 2001) have also linked spring bloom initiation to offshore advection, eddy-induced upwelling or river runoff. Finally, oceanic convection has been found
105 responsible for a significant vertical transport, thus maintaining a winter stock of phytoplankton in the deep mixed layer that can potentially re-seed the spring bloom (Backhaus et al., 1999, 2003).

Behrenfeld (2010) adopted a different approach by examining the influence of dynamic top-down controls, suggesting the “dilution-recoupling hypothesis”. This is a concept that is implicit in Evans and Parslow (1985)’s model. Behrenfeld (2010)’s hypothesis proposes that a vertically integrated
110 biomass increases in mid-winter with the increase of day length, even when the mixed layer depth is at its deepest, and reaches its maximum with the recoupling of grazers due to stratification. Unfortunately, as also noted by Behrenfeld (2010), data on top-down controls remain elusive at the spatial and temporal resolutions necessary to test this hypothesis against the complex structure of North Atlantic phytoplankton seasonality.

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1.4 When and why does a surface bloom start?

As noted by Cole et al. (2015), assessing the drivers of bloom initiation variability may lead to the understanding of what starts the bloom in the first place. Despite all of the above mentioned hypotheses, there is still no clear consensus regarding a single main driver of North Atlantic spring
120 blooms. Additionally, the spatial application of these theories may not hold true in smaller regions, where local forcing plays a more important role. Nonetheless, the key process, and common to all hypotheses of surface bloom initiation, is based on the spring stabilization of the water column, where both light and nutrients are at sufficient levels: whether by mixed layer shoaling (Sverdrup, 1953), or by weakening turbulent mixing (Huisman et al., 1999, 2002; Taylor and Ferrari, 2011a;
125 Townsend et al., 1994; Taylor and Ferrari, 2011b). Their main differences reside in the physical proxy for bloom initiation: what physical indicator best predicts bloom timing?

While there are a number of metrics that can be used to delineate bloom initiation (Yoder and Kennelly, 2003; Siegel et al., 2002; Rolinski et al., 2007), our goal to seek a metric that can be credibly related to the processes proposed above, *i.e.* those that relate to the preconditioning of the water column prior to surface bloom initiation. In this, any metric that uses the bloom peak (such as the popular 5 % above annual median (Siegel et al., 2002)), or seasonally integrated chlorophyll, will be handicapped because it inherently takes into account not only what starts the bloom, but also what terminates it some weeks or months later. We seek instead a phenology metric that is not confounded by the bloom peak, does not require winter values, and is a straightforward indicator of the greening of the surface ocean as observed from space. Our metric is based on how advance or delayed the development of surface chlorophyll concentration is in a particular year compared to the climatological date and rate of maximum concentration increase.

We construct four models based on the literature using a range of physical observations, primarily from satellite but also model data, and describe key processes observed in the North Atlantic (Table 1 and Figure 1). In each case, we make the models as simple as possible - capturing the essential process dynamics in terms of at most two observable/estimated fields only.

We use the Information Theoretic (IT) approach to investigate which model for surface blooms has the most support within the North Atlantic. The IT approach is a very useful tool when comparing different models. In particular, it provides a rigorous framework for evaluating the evidence in support of competing models. It does so by defining *a priori* a set of “multiple working hypotheses” rather than a single alternative to the null hypothesis. The IT approach is then followed by expressing each hypothesis in quantitative terms that represent their strength of evidence to be further used in the model selection (Burnham et al., 2011).

We conduct our study focusing on bottom-up controls that may trigger a North Atlantic phytoplankton surface bloom, and thus neglect the effect of top-down controls (grazing, (Behrenfeld, 2010; Evans and Parslow, 1985; Irigoien et al., 2005)). Information on top-down controls is not available at the spatial and temporal coverage needed to assess mesoscale physical forcing. In addition, as Chiswell (2011) shows, the seasonal cycle of surface chlorophyll differs from the vertically-integrated chlorophyll. Behrenfeld (2010)’s “dilution-recoupling hypothesis” applied to vertically-integrated chlorophyll blooms, while the other hypotheses (Sverdrup, 1953; Siegel et al., 2002; Platt et al., 1991; Huisman et al., 1999; Huisman and Sommeijer, 2002; Huisman et al., 2002; Townsend et al., 1994; Taylor and Ferrari, 2011a, b) can be applied to surface chlorophyll. Our aim is to compare the latter ones, in which it is assumed that surface blooms only take off when the surface waters stabilise.

160 **2 Material and Methods**

2.1 Information Theoretic (IT) Approach

The main aspects of the IT framework (Burnham et al., 2011; Burnham and Anderson, 2002; Akaike, 1973) in the context of our study include (1) identifying plausible mechanistic hypotheses, and (2) a strong reliance on the quantitative evidence of factor(s) affecting a response variable, rather than 165 a formal assessment of the statistical significance of such factor(s). In our study, (1) is expressed through mathematical descriptions of the different hypotheses to be tested (see Table 1 and Section 2.2), while (2) is covered by ranking the spatial evidence of the models using the concept of model selection and multimodel inference (see Burnham et al. (2011) and Section 2.5).

2.2 Physical mechanisms

170 We are particularly interested in knowing how much information from raw data is correlated to surface chlorophyll. Raw data refers to the original data in their simplest form, without pre-processing. Therefore, we quantitatively translate the fundamental physical processes that can be used to predict a phytoplankton surface bloom in the North Atlantic into simple and straight-forward models (Table 1 and Figure 1).

175 **Critical depth** - A bloom initiates if the mixed layer depth (MLD, H) shoals below the critical depth, so light (photosynthetically active radiation, PAR, L) becomes available to phytoplankton cells (Figure 1a) (Sverdrup, 1953; Siegel et al., 2002; Platt et al., 1991). Therefore, L integrated over the H provides an estimate of the light available within the euphotic depth for phytoplankton to grow.

180 **Critical turbulence** - A bloom initiates if there is a balance between buoyancy (heat flux, Q) and wind-driven mixing (M , Figure 1b) (Huisman et al., 1999; Huisman and Sommeijer, 2002; Huisman et al., 2002).

Critical light exposure - A bloom initiates if wind-driven mixing (M) is at a low enough level to allow cells to experience surface light conditions (L , Figure 1c) (Townsend et al., 1994).

185 **Critical heat flux** - Bloom initiation is associated with the date when net warming starts ($Q \geq 0$), and low wind-driven mixing (M) increases the residence time of phytoplankton in the euphotic layer (Figure 1d) (Taylor and Ferrari, 2011a, b).

2.3 Data sets

In order to gather the information necessary to formulate the models for the North Atlantic domain, 190 we used satellite observations (chlorophyll concentration, attenuation coefficient and photosynthet-

ically active radiation), model estimations for the variables where satellite data was not available (mixed layer depth), and model and observational merged data (wind stress and heat flux).

We used products derived from the European Node for Global Ocean Colour (GlobColour Project, <http://www.globcolour.info/>). The GlobColour Project blends observational data from the Sea-viewing
195 Wide Field-of-view Sensor (SeaWiFS), the Moderate Resolution Imaging Spectroradiometer (MODIS-AQUA), and the Medium Resolution Imaging Spectrometer (MERIS) instruments by using the Garver-Siegel-Maritorena (GSM) algorithm (Maritorena et al., 2002) to generate a merged, global ocean colour product. Combining the three sensors increases the data coverage in both time and space, thus providing significantly elevated spatio-temporal coverage (Maritorena et al., 2010), making
200 it a common choice for phenology studies (Cole et al., 2012; Kahru et al., 2011). For this study, we chose to use daily, $1/4^\circ$ resolution level 3 mean chlorophyll concentration (C) and attenuation coefficient (K_d) products (based on the analysis performed by Ferreira et al. (2014)), from 1998 to 2010 inclusive, thus providing a total of 13 years of data.

The surface photosynthetically active radiation (PAR, L) was obtained from the SeaWifs data
205 center (<http://oceancolor.gsfc.nasa.gov/>). We used daily, 9 km resolution product from 1998 to 2010. These data were further gridded onto $1/4^\circ$ using linear interpolation to match the spatial resolution of the other data sets.

The mixed layer PAR (L_H) was defined as L integrated from the surface to the depth of the mixed layer H :

$$210 \quad L_H = \frac{L}{HK_d} (1 - e^{-HK_d}) \quad (1)$$

using the relevant K_d reported by Irwin et al. (2012) and Cole et al. (2015).

Mixed layer depth (MLD, H) data were obtained from TOPAZ 4 reanalysis (Sakov et al., 2012). The TOPAZ system is a coupled ocean-sea ice data simulation system for the North Atlantic and Arctic Ocean with a resolution of 12-16 km, and is the main forecasting system for the Arctic
215 Ocean in Copernicus (<http://www.myocean.eu>) and the Norwegian contribution to the Global Ocean Data Assimilation Experiment (GODAE). It uses the Hybrid Coordinate Ocean Model (HYCOM, <http://hycom.org/hycom/>) (Bleck, 2002). HYCOM is coupled to a EVP sea ice model (Hunke and Dukowicz, 1997) and a thermodynamic module (Drange et al., 1996). The model assimilates sea surface temperature, altimetry, ice concentration, ice drift, and available *in situ* measurements with
220 the ensemble Kalman Filter (Evensen, 2003). The model daily output is binned onto a $1/4^\circ$ regular grid. The MLD is calculated using a density criteria with a threshold of 0.01 kg m^{-3} (Petrenko et al., 2013) from 1998 to 2010.

Wind stress (τ_{wind}) is used as a measure for wind-driven mixing (M) (Simpson et al., 1981; Taboada and Anadón, 2014) and was estimated by using: $M \propto |\tau_{wind}|^{3/2}$, which is proportional to
225 the power exerted by the wind on the surface ocean and the turbulent kinetic energy used in Brody and Lozier (2014)'s calculations of the mixing length scale.

Both τ_{wind} and heat flux (Q) data were gathered on a spatial resolution of $1.875^\circ \times 1.905^\circ$ from the National Centers for Environmental Prediction (NCAR) and the National Center for Atmospheric Research (NCEP) (Kalnay et al., 1996). These data sets were further gridded onto $1/4^\circ$ using linear interpolation to match the spatial resolution of the other data sets.

All data sets started on October 1, 1997. We only focused on latitudes north of 40°N due to the fact that lower latitudes have a less well-defined seasonal cycle (Follows and Dutkiewicz, 2011; Brody and Lozier, 2014).

2.4 Metrics

One of the fundamental aspects of spring bloom is the rapid increase in surface chlorophyll concentration; a phenomenon that can be interpreted as bloom initiation. In this work, we choose a bloom initiation metric that relates to how advanced or delayed the surface chlorophyll concentration is in a particular year, compared to the climatological date of maximum surface concentration increase. We term this the rate of change phenology anomaly (RPA, R). This metric has the advantage of not depending on the maximum chlorophyll concentration (an indicator of the peak of the bloom). Neither does it depend on winter values, which are usually missing from remote sensing products (Ferreira et al., 2014); or on vertical integration (Behrenfeld, 2010); all of which introduce extraneous factors into the mechanistic reasoning as to the onset of a bloom. These are all limitations that occur in many other metrics used in the literature (Siegel et al., 2002; Sharples et al., 2006; Brody and Lozier, 2014). We decided to use an anomaly of surface chlorophyll because it is a more relevant measure in regards to higher trophic levels and is one we believe is closer to bloom preconditioning. Additionally, in order to use an integrated chlorophyll field, we would need to use modelled mixed layer depth, which is incompatible with testing one of our key models.

At each location x, y (each $1/4^\circ$ pixel), we estimate the climatological pattern of surface chlorophyll concentration $\bar{C}(x, y, t)$ by applying a generalized additive model (GAM) to the observations from 1998 to 2010 (Figure 2). We then calculate the day of the year where the climatological mean exhibits the maximum rate of increase $g(x, y) = \max\{d\bar{C}/dt\}$. We define the climatological date of maximum increase as $T_0 = t : d\bar{C}/dt = g$, and the climatological chlorophyll concentration on that day we define as $\bar{C}_0 = \bar{C}(x, y, T_0)$. For each year i and location x, y , we fit a GAM with a smooth spline on the period $T_0 \pm 15$ days for observed surface chlorophyll to produce $C'_i(x, y, t)$. Lastly we define the rate of change phenology anomaly as $R_i(x, y) = \frac{C'_i(x, y, T_0) - \bar{C}(x, y, T_0)}{g(x, y)}$. Thus, the RPA metric $R_i(x, y)$ is a value in days and relates to how advanced or delayed the seasonal development of chlorophyll concentration is in each year i compared to the climatology of the bloom. We set a threshold that at least 3 observations must exist within the 30-day window for the RPA method to be valid. We apply a spatial kriging with a maximum radius of 250 km to fill in pixels where the method cannot be used, *e.g.* due to missing data around T_0 in some years, or low seasonality.

We investigated the spatially dependent ranking of the models (Table 1 and Figure 1) using the IT approach. Thus, we constructed indicator fields and time series which, in various combinations, provide models consistent with the principle physical dynamics observed in the North Atlantic. At 265 each location, we apply a centered moving average of 30 days to the physical driver observations and these will be referred to as L' , L'_H , M' and Q' . We also use Q'_0 for the date when Q' becomes positive (start of net warming) and remains positive for seven consecutive days. We further applied an inverse distance weighted interpolation (using the weighted average of the values at the known pixels) to all thresholds to fill in the pixels where the thresholds could not be estimated. All pixels in waters 270 shallower than 200 m were removed as coastal regions have higher associated biases (Maritorena et al., 2010) due to high turbidity and consequent different optical properties (McCain et al., 2006; Antoine et al., 1996; Longhurst et al., 1995; Sathyendranath et al., 2001).

2.5 Analysis

There are several model selection tools that can be used for comparing and ranking models. In our IT 275 approach, we used the Akaike Information Criterion (AIC) (Burnham et al., 2011), which is based on the residual sum of squares (RSS) from each model. By comparing and ranking the evidence from different models, their relative importance can be quantified. Since we only aimed at assessing 13 years of data (from 1998 to 2010), we used the AICc. The AICc is the AIC corrected for small samples. Theoretically, as sample size increases, AICc converges to AIC. Another model selection 280 unit is the Akaike weight, which can be either based on the AIC or the AICc. The Akaike weight is a value between 0 and 1 representing the weighted mean probability of each model, *i.e.* the strength of evidence in support of each model.

Each model was formulated as a regression as shown in Table 1. Based on the weight of each model, we could select the most supported model for each $1/4^\circ$ pixel.

285 3 Results

From the four hypotheses considered (critical depth; critical turbulence; critical light exposure, and critical heat flux) within each $1/4^\circ$ pixel, the one with the highest Akaike weight is selected as the winning hypothesis (Figure 3), where we see that the critical depth seems to be the most frequent winning hypothesis.

290 The spatial distribution of winning hypotheses shows no systematic pattern with regards to basin, depth, or latitude (Figure 3). We also ran this analysis with two other bloom timing metrics: 5 % above annual median (Siegel et al., 2002; Racault et al., 2012; Henson et al., 2010) and maximum increase in chlorophyll concentration (Rolinski et al., 2007; Sharples et al., 2006; Wiltshire et al., 2008) and we found similar results: no systematic pattern (results not shown).

295 In spite of the general dominance of the critical depth hypothesis, there are, however, regions that
show some coherency: the critical turbulence appears to be well supported mainly off Newfoundland;
the critical heat flux has local support north of Iceland and in the Labrador Sea; the critical light
exposure appears to have a wider distribution with very low frequencies. Spatial distribution of
Akaike weights (Figure A1) indicate the strength of support for the "winning" hypothesis. There
300 are regions where the weights are close to 1, indicating that the corresponding models are clear
winners. Some of these regions are the same as the ones observed in Figure 3: for instance, offshore
of Newfoundland, suggesting a strong support for the critical turbulence hypothesis in this region.

305 A pixel-wise multimodel inference approach also allows the quantification of the number of oc-
currences of each of the four alternative hypotheses as the winning (Figure 3). There are no clear
differences in the ranking units of the three less frequent hypothesis (0.15, 0.11 and 0.07), whilst the
critical depth showed a higher ranking unit (0.67).

310 To better understand the effect of each physical component (L'_H , L' , M' , Q' , Q'_0) within the four
hypotheses (Figure 1), we built single-variable models (linear regressions) using each component as
variable for each location (Figure 4). The most frequent winning physical driver based on the Akaike
weights is heat flux Q' . Its spatial distribution dominates off Newfoundland, in the subpolar gyre and
intermediate gyre regions, and in the Bay of Biscay. Its dominance is however only slightly greater
than the other physical components.

4 Discussion

315 The phenology of spring bloom characteristics (e.g. initiation, peak) is thought to be controlled
by a number of mechanisms including bottom-up and top-down processes. Here we specifically
set out to test various bottom-up processes that can be used as indicators of phytoplankton surface
blooms, testing several simplified hypotheses across a broad extent of the North Atlantic. In this
regard, spring surface bloom initiation is problematic in that defining it has as much to do with
what limits the bloom amplitude as what starts it in the first place. Moreover, limiting factor(s)
320 can be the ultimate switching mechanism needed for a bloom to start. Instead, we seek to explain
what bottom-up processes determine the interannual variability of bloom development around the
time where, climatologically, one would expect the maximum rate of increase in surface chlorophyll
concentration. By quantifying each physical mechanism independently, we observe that, even though
there is no clear losing mechanism in the North Atlantic domain, Sverdrup (1953)'s classical theory
325 (critical depth) still dominates; *i.e.* it has a superior evidence supporting the interannual variability
of timing across the greatest range of space in the North Atlantic (Figure 3).

All of the four alternative hypotheses are expressed as simple interpretations of what potentially
drives the surface blooms in the North Atlantic at the mesoscale (Figure 1). The models are con-
structed so as to be as simple as possible, using at most two physical observables (light intensity,

330 light intensity integrated over the mixed layer depth, wind-driven mixing and heat flux) in various combinations. Each model is based on one of the two classes of mechanisms discussed in the introduction: mixed layer shoaling (critical depth) or active mixing (critical turbulence, critical light exposure and critical heat flux). Our study shows the strength of the critical depth model and indicates a dominance of the mixed layer shoaling over the active mixing mechanism, but not everywhere.

335 There is an apparent inconsistency between our results and some recently reported results, notably by Cole et al. (2015) and Brody and Lozier (2014). In the former, the strongest relationship with bloom initiation was found with the date of zero heat flux (Q'_0), while in the latter it was with the shoaling of mixing length (essentially heat flux tempered by wind stress and stratification). There are however several reasons why the results may differ. Firstly, Brody and Lozier (2014) tested the

340 climatological bloom initiation date against the various drivers in a spatial context, rather than the interannual variations in a temporal context as we do here. In contrast, Cole et al. (2015), while maintaining the temporal aspect, reduced each seasonal cycle of potential drivers to a single annual metric, *e.g.* the date when the mixed layer depth shoals most rapidly. Precisely how these different aggregation processes influence the outcome of statistical treatments remains unresolved. More im-

345 portantly, the bloom initiation metric chosen by each of these studies are also different. Cole et al. (2015) chose the 5% above annual median as their metric (Siegel et al., 2002); a metric that may be less than reliable with regards to bloom initiation. Brody and Lozier (2014) used the date of first increase of surface chlorophyll concentration (F'_0), specifically given by $F'_0 = t : d\bar{C}/dt = 0$ rather than our date of maximum increase $T_0 = t : d\bar{C}/dt = g$. While it may be debated as to which of these

350 have greater significance (and for which ecosystem process), it also underscores an important issue; that different milestones in the seasonal development of the spring bloom may well come under the influence of different dynamics.

In our study, even though the critical depth hypothesis is the winner (most spatially frequent), the spatial distribution of the winning model shows regions where the mixed layer shoaling mechanism

355 seems not to be supported. For instance, there is a dominance of the critical turbulence and critical light exposure models in the Bay of Biscay. This may be due to the high degree of upwelling in this region; hence the failure of critical depth hypothesis to predict surface bloom dynamics. Another example occurs east of Newfoundland, where the critical turbulence and critical heat flux hypotheses dominate. Both of these hypotheses have wind-driven mixing as a common parameter. In addition,

360 heat flux and light intensity are also key individual drivers in this region (as confirmed in Figure 4). These findings suggest that spring bloom seasonality in these regions may be driven by periods of reduced active turbulent mixing, increasing exposure to light (Huisman et al., 1999; Taboada and Anadón, 2014). The region off Newfoundland is also very energetic (high physical forcing), highly influenced by the subpolar gyre, and serves as a path for the northward movement of the Gulf

365 Stream waters. The failure of critical depth to explain the bloom dynamics in this region may be due to subduction of cold waters from the subpolar gyre and the warm waters from the North Atlantic

drift. This may explain why the critical turbulence and the critical heat flux were dominating in the region east of Newfoundland and into the central North Atlantic. These 3D processes should be tested in the future to help understand the dynamics of the North Atlantic system.

370 The explanatory power of the hypotheses that assume the mechanism of active mixing (critical turbulence; critical light exposure and critical heat flux) is fairly evenly distributed (Figure 3). These three hypotheses seem to operate with a switch-on mechanism, *i.e.* a number of conditions has to be met for bloom growth, and any one may be the critical condition that triggers the growth spurt. This interpretation is supported by comparing Figures 3 and 4, where the critical depth model is a
375 clear winner in the model inter-comparison, but only scores average when tested against individual parameters. In this case, the limiting conditions appear to be either light intensity or heat flux (since all three have wind-driven mixing as a common parameter). Our results show that there is no clear winning hypothesis among these three active mixing models, but there is a bias towards mechanisms involving heat flux (Figure 4). This finding is supported by Taylor and Ferrari (2011a),
380 where a bloom develops due to the start of net warming, weakening turbulent mixing, and subsequent increase of the residence time of phytoplankton cells within the euphotic layer. In order for this to happen, a standing stock of phytoplankton cells needs to exist *a priori*. The “seed stock” is the left overs from the previous year that have been surviving all winter at depth due to convection. As suggested by Backhaus et al. (2003, 1999) and Chiswell (2011), deep convection spreads out the
385 overwintering remnants, but, as soon as stratification comes in, those lucky enough to be in the surface start to bloom. From our results (Figure 3), we confirm that heat flux is a strong physical driver. Thus, in regions where the critical depth is not the winning model, the active mixing mechanism (either triggered by light intensity or heat flux) seems to play an important role.

The second most common physical property was wind-driven mixing (Figure 4) and is the common parameter in the models concerning the active mixing mechanism. In the past, the importance of wind-driven mixing has been shown by Huisman et al. (1999); Huisman and Sommeijer (2002) and Huisman et al. (2002), and confirmed by Taylor and Ferrari (2011a, b). The first group of authors stresses a balance between wind-driven mixing and sinking rates, so that an intermediate mixing allows both enough surface nutrient replenishment, and sufficient average light exposure. Recently,
395 Taboada and Anadón (2014) suggested that wind forcing (wind stress as a proxy for wind surface mixing) played a key role in bloom timing and magnitude (see their Figures 5a and 5c). The results shown by these authors are based on single-parameter hypotheses (not including heat flux) and confirm that spring blooms are triggered by different physical properties in different mesoscale regions. Our results are thus in agreement, where wind stress is found as a common parameter within the
400 North Atlantic domain.

Winds have essentially two effects: turbulent mixing (Backhaus et al., 2003; Townsend et al., 1994) which is only shallow (around 50 m in mid-latitudes), and surface cooling which promotes deep convection (Backhaus et al., 2003; Brody and Lozier, 2014). Together with the cessation of

convective overturn, wind stress decreases during the spring. Deep mixing is therefore no longer active, and there is a shift from a deep-mixed regime to a shallow light-driven regime. However, it is important to note that the depth of the mixed layer is not the same as the depth of vertical mixing of plankton (Chiswell, 2011). These two depths only match when vertical mixing is at its limit (Taylor and Ferrari, 2011a). In the presence of low vertical mixing, a surface bloom can initiate even if critical depth conditions (Sverdrup, 1953) are not met, *i.e.* even if the thermocline is deeper than the critical depth. This mechanism is presented by Chiswell (2011) as the “stratification-onset model”, in which the author contends that the critical depth hypothesis is valid during autumn and winter, when the deepening thermocline may suppress production due to downward mixing of plankton, but not in spring, since the upper layers are not well mixed in plankton. The model is consistent with the findings by Taylor and Ferrari (2011a), in which surface stratification results from cessation of convective overturn and low wind stress. In our study, we show that the critical depth hypothesis is still valuable to predict phytoplankton spring surface blooms in the North Atlantic.

Our findings have, however, assumptions that are worth considering. Firstly, we based the critical depth hypothesis on Sverdrup’s classical theory, thus only accounting for L_H . This makes the model inherently simpler. The other three hypotheses use two parameters separately, and are therefore somewhat handicapped (higher penalty due to higher number of parameters) when compared to the critical depth. We believe that this type of study would improve if similar combinations would be found for the remaining hypotheses: critical turbulence, critical light exposure and critical heat flux. For this reason, we tried to use a two-parameter approach (considering H' and L' separately) for the critical depth hypothesis, so that the four models would have the same number of parameters, and thus the AICc weights would be comparable. The critical depth explained by L'_H alone showed to be inherently superior (with a much stronger signal) than the combined H and L model, thus we chose to keep our interpretation of the critical depth hypothesis using L_H . This underscores the point that physical reasoning can come a long way in improving model predictions.

Secondly, we recognise that our study assumes that the same mechanism predicts surface bloom timing at a given location for the entire time frame (from 1998 to 2010). However, it is conceivable that different mechanisms may be best predictors in different years. Considering the high variability in the spatial distribution of the models (Figure 3), it is reasonable to expect similar high temporal variability. In the same way we observe that different mechanisms dominate in different regions, intuitively, one can assume that different mechanisms will also dominate in different years. Indeed, given the scatter in winning models, it is entirely conceivable that bloom timing is governed by a limiting factor; that multiple conditions have to be met, any one of which may be the trigger in any given year or location.

Thirdly, we also recognise that our study fails at assessing top-down mechanisms. A key hypothesis that has been attempted by Brody and Lozier (2014) is the “dilution-recoupling hypothesis”

(Behrenfeld, 2010). Brody and Lozier (2014) found very little correspondence between seasonal thermocline increases and integrated chlorophyll increases. However, as they noted, in order to successfully study this hypothesis, one would require temporally and spatially distributed data on grazing pressure and encounter rates between grazers and phytoplankton. Since such highly-resolved
445 data sets are not available, top-down mechanisms cannot be properly assessed at this time.

5 Conclusions

The complexity of spring bloom dynamics in the North Atlantic has been discussed since Sverdrup (1953) published the “critical depth hypothesis”. The discussion took a different direction when Behrenfeld (2010) suggested a top-down control of the phytoplankton seasonal cycle with
450 the “dilution-recoupling hypothesis”. Various studies followed the same line of thought (Behrenfeld et al., 2013c, a, b; Irigoien et al., 2005). However, bottom-up factors are still the most studied (Siegel et al., 2002; Huisman et al., 1999; Townsend et al., 1994; Taylor and Ferrari, 2011a), especially because data is more readily available than for top-down factors. All these theories (Figure 1) are not necessarily contradictory. Instead, each one adds a missing element necessary to fully understand
455 spring bloom dynamics (Lindemann and St John, 2014). Even though satellite observations have provided great insight over the last decades, the picture is still one of complexity. Our study thus confirms that a single hypothesis for what drives a North Atlantic spring bloom may be too simplistic.

A consensus is yet to be reached regarding the onset of spring phytoplankton blooms in the North
460 Atlantic. Every theory published in the literature claims to best predict the timing of the spring bloom. However, one cannot adopt a single hypothesis simply because all of the theories seem to apply, either at shorter temporal or spatial scales. By revisiting four of the main hypotheses on the subject, we are able to confirm that phytoplankton surface bloom dynamics in the highly-variable North Atlantic are far too complex to be driven by the same mechanism in all places and in all
465 years. We show that, in terms of bottom-up processes alone, there is a dominant physical mechanism (mixed layer shoaling) that best predicts the growing phase of North Atlantic phytoplankton blooms at the mesoscale. However, some regions show coherent patterns, supporting the idea that there are distinct physical phenomena driving spring surface blooms, rather than a single one. We believe these findings to be relevant for the ongoing discussion on North Atlantic bloom onset.

470 Appendix A: Appendix A

Figure A1 - Map of the Akaike weights of the winner model.

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ftp.acri.fr/, supported by EU FP7 MyOcean and ESA GlobColor projects, using ESA ENVISAT MERIS, NASA
475 MODIS and SeaWiFS data. PAR was obtained from the SeaWiFS data center available at <http://oceancolor.gsfc.nasa.gov/>. MLD was obtained from the Hybrid Coordinate Ocean Model (HYCOM) available at <http://hycom.org/hycom/>. Wind stress and heat flux were obtained from the Earth System Research Laboratory, Physical Sciences Division, and are available at <http://www.esrl.noaa.gov/psd/data/gridded/tables/daily.html>. This paper is a deliverable of the Nordic Centre for Research on Marine Ecosystems and Resources under Climate Change (NorMER), which is funded by the Norden Top-level Research Initiative sub-programme “Effect Studies and Adaptation to Climate Change”. AWV acknowledges the Danish Council for Strategic Research and its support for the NAACOS project. The research leading to these results has received funding from the European Union 7th Framework Programme (FP7 2007-2013) under grant agreement number 308299 (NAACLIM project).

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485 **References**

Akaike, H.: Information theory as an extension of the maximum likelihood principle, pp. 267–281, Akadémiai Kiado, Budapest, 1973.

Antoine, D., Andre, J., and Morel, A.: Oceanic primary production 2. Estimation at global scale from satellite (coastal zone color scanner) chlorophyll, *Global biogeochemical cycles*, 10, 57–69, 1996.

490 Backhaus, J. O., Wehde, H., Hegseth, E. N., and Kämpf, J.: 'Phyto-convection': the role of oceanic convection in primary production, *Marine Ecology Progress Series*, 189, 77–92, 1999.

Backhaus, J. O., Hegseth, E. N., Wehde, H., Irigoien, X., Hatten, K., and Logemann, K.: Convection and primary production in winter, *Marine Ecology Progress Series*, 251, 1–14, 2003.

Badcock, J. and Merrett, N. R.: Midwater fishes in the eastern North Atlantic—I. Vertical distribution and associated biology in 30 N, 23 W, with developmental notes on certain myctophids, *Progress in Oceanography*, 7, 3–58, 1976.

Behrenfeld, M. J.: Abandoning Sverdrup's Critical Depth Hypothesis on phytoplankton blooms, *Ecology*, 91, 977–989, 2010.

Behrenfeld, M. J., Boss, E. S., and Banse, K.: Resurrecting the Ecological Underpinnings of Ocean Plankton Blooms, *Annual Review of Marine Science*, 6, 16.1–16.28, 2013a.

500 Behrenfeld, M. J., Doney, S. C., Lima, I., Boss, E. S., and Siegel, D. A.: Annual cycles of ecological disturbance and recovery underlying the subarctic Atlantic spring plankton bloom, *Global biogeochemical cycles*, 27, 526–540, doi:10.1002/gbc.20050, 2013b.

Behrenfeld, M. J., Doney, S. C., Lima, I., Boss, E. S., and Siegel, D. A.: Reply to a comment by Stephen M. Chiswell on: "Annual cycles of ecological disturbance and recovery underlying the subarctic Atlantic spring plankton bloom" by MJ Behrenfeld et al. (2013), *Global Biogeochemical Cycles*, 27, 1294–1296, 2013c.

Bleck, R.: An oceanic general circulation model framed in hybrid isopycnic-Cartesian coordinates, *Ocean modelling*, 4, 55–88, 2002.

510 Brody, S. R. and Lozier, M. S.: Changes in dominant mixing length scales as a driver of subpolar phytoplankton bloom initiation in the North Atlantic, *Geophysical Research Letters*, 41, 3197–3203, 2014.

Brody, S. R., Lozier, M. S., and Dunne, J. P.: A comparison of methods to determine phytoplankton bloom initiation, *Journal of Geophysical Research*, 118, 2345–2357, 2013.

Burnham, K. P. and Anderson, D. R.: Model selection and multimodel inference: a practical information-theoretic approach, Springer, New York, 2002.

515 Burnham, K. P., Anderson, D. R., and Huyvaert, K. P.: AIC model selection and multimodel inference in behavioral ecology: some background, observations, and comparisons, *Behavioral Ecology and Sociobiology*, 65, 23–35, 2011.

Chiswell, S. M.: Annual cycles and spring blooms in phytoplankton: don't abandon Sverdrup completely, *Marine ecology progress series*, 443, 39–50, 2011.

520 Chiswell, S. M., Bradford-Grieve, J., Hadfield, M. G., and Kennan, S. C.: Climatology of surface chlorophyll a, autumn-winter and spring blooms in the southwest Pacific Ocean, *Journal of Geophysical Research: Oceans*, 118, 1003–1018, 2013.

525 Cole, H., Henson, S., Martin, A., and Yool, A.: Mind the gap: The impact of missing data on the calculation of phytoplankton phenology metrics, *Journal of Geophysical Research*, 117, C08030, doi:10.1029/2012JC008249, 2012.

526 Cole, H. S., Henson, S., Martin, A. P., and Yool, A.: Basin-wide mechanisms for spring bloom initiation: how typical is the North Atlantic?, *ICES Journal of Marine Science: Journal du Conseil*, p. fsu239, doi:10.1093/icesjms/fsu239, 2015.

530 Drange, H., Simonsen, K., Environmental, N., and Center, R. S.: Formulation of air-sea fluxes in the ESOP2 version of MICOM, Nansen Environmental and Remote Sensing Center, Norway, 1996.

535 Evans, G. T. and Parslow, J. S.: A model of annual plankton cycles, *Biological Oceanography*, 3, 327–347, 1985.

540 Evensen, G.: The ensemble Kalman filter: Theoretical formulation and practical implementation, *Ocean dynamics*, 53, 343–367, 2003.

545 Ferreira, A. S. A., Visser, A. W., MacKenzie, B. R., and Payne, M. R.: Accuracy and precision in the calculation of phenology metrics, *Journal of Geophysical Research: Oceans*, 119, doi:10.1002/2014JC010323, <http://dx.doi.org/10.1002/2014JC010323>, 2014.

550 Field, C., Behrenfeld, M., Randerson, J., and Falkowski, P.: Primary production of the biosphere: integrating terrestrial and oceanic components, *Science*, 281, 237–240, 1998.

555 Follows, M. J. and Dutkiewicz, S.: Modeling Diverse Communities of Marine Microbes, *Annual Review of Marine Science*, 3, 427–451, 2011.

560 Frajka-Williams, E. and Rhines, P. B.: Physical controls and interannual variability of the Labrador Sea spring phytoplankton bloom in distinct regions, *Deep Sea Research Part I: Oceanographic Research Papers*, 57, 541–552, 2010.

565 Gaard, E.: Seasonal abundance and development of *Calanus finmarchicus* in relation to phytoplankton and hydrography on the Faroe Shelf, *ICES Journal of Marine Science: Journal du Conseil*, 57, 1605–1611, 2000.

570 Garçon, V. C., Oschlies, A., Doney, S. C., McGillicuddy, D., and Waniek, J.: The role of mesoscale variability on plankton dynamics in the North Atlantic, *Deep Sea Research Part II: Topical Studies in Oceanography*, 48, 2199–2226, 2001.

575 Gislason, A. and Silva, T.: Abundance, composition, and development of zooplankton in the Subarctic Iceland Sea in 2006, 2007, and 2008, *ICES Journal of Marine Science: Journal du Conseil*, 69, 1263–1276, 2012.

580 Heath, M. R., Fraser, J. G., Gislason, A., Hay, S. J., Jónasdóttir, S. H., and Richardson, K.: Winter distribution of *Calanus finmarchicus* in the Northeast Atlantic, *ICES Journal of Marine Science: Journal du Conseil*, 57, 1628–1635, 2000.

585 Henson, S., Sarmiento, J., Dunne, J., Bopp, L., Lima, I., Doney, S., John, J., and Beaulieu, C.: Detection of anthropogenic climate change in satellite records of ocean chlorophyll and productivity, *Biogeosciences*, 7, 621–640, 2010.

590 Huisman, J. and Sommeijer, B.: Maximal sustainable sinking velocity of phytoplankton species, *Marine ecology progress series*, 244, 39 – 48, 2002.

595 Huisman, J., Oostveen, P. v., and Weissing, F. J.: Critical Depth and Critical Turbulence: Two Different Mechanisms for the Development of Phytoplankton Blooms, *Limnology and oceanography*, 44, 1781–1787, 1999.

Huisman, J., Arrayás, M., Ebert, U., and Sommeijer, B.: How Do Sinking Phytoplankton Species Manage to Persist?, *The American Naturalist*, 159, 245–254, 2002.

Hunke, E. and Dukowicz, J.: An elastic-viscous-plastic model for sea ice dynamics, *Journal of Physical Oceanography*, 27, 1849–1867, 1997.

565 Irigoien, X., Flynn, K., and Harris, R.: Phytoplankton blooms: a ‘loophole’ in microzooplankton grazing impact?, *Journal of Plankton Research*, 27, 313–321, 2005.

Irwin, A. J., Nelles, A. M., and Finkel, Z. V.: Phytoplankton niches estimated from field data, *Limnology and oceanography*, 57, 787–797, 2012.

570 Kahru, M., Brotas, V., Manzano-Sarabia, M., and Mitchell, B.: Are phytoplankton blooms occurring earlier in the Arctic?, *Global Change Biology*, 17, 1733–1739, 2011.

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., and Woollen, J.: The NCEP/NCAR 40-year reanalysis project, *Bulletin of the American meteorological Society*, 77, 437–471, 1996.

575 Lévy, M., Lehahn, Y., André, J.-M., Mémery, L., Loisel, H., and Heifetz, E.: Production regimes in the northeast Atlantic: A study based on Sea-viewing Wide Field-of-view Sensor (SeaWiFS) chlorophyll and ocean general circulation model mixed layer depth, *Journal of Geophysical Research-Oceans*, 110, C07S10, doi:10.1029/2004JC002771, 2005.

Lindemann, C. and St John, M.: A seasonal diary of phytoplankton in the North Atlantic, *Frontiers in Marine Science*, 1, 1–6, 2014.

580 Longhurst, A.: Seasonal cycles of pelagic production and consumption, *Progress in Oceanography*, 36, 77–167, 1995.

Longhurst, A., Sathyendranath, S., Platt, T., and Caverhill, C.: An estimate of global primary production in the ocean from satellite radiometer data, *Journal of Plankton Research*, 17, 1245–1271, 1995.

585 Mahadevan, A., D’Asaro, E., Lee, C., and Perry, M. J.: Eddy-Driven Stratification Initiates North Atlantic Spring Phytoplankton Blooms, *Science*, 337, 54–58, 2012.

Maritorena, S., Siegel, D. A., and Peterson, A. R.: Optimization of a semianalytical ocean color model for global-scale applications, *Applied Optics*, 41, 2705–2714, 2002.

590 Maritorena, S., d’Andon, O. H. F., Mangin, A., and Siegel, D. A.: Merged satellite ocean color data products using a bio-optical model: Characteristics, benefits and issues, *Remote Sensing of Environment*, 114, 1791–1804, 2010.

Martinez, E., Antoine, D., D’Ortenzio, F., and de Boyer Montegut, C.: Phytoplankton spring and fall blooms in the North Atlantic in the 1980s and 2000s, *Journal of Geophysical Research*, 116, C11 029, doi:10.1029/2010JC006836, 2011.

595 McCain, C., Hooker, S., Feldman, G., and Bontempi, P.: Satellite data for ocean biology, biogeochemistry, and climate research, *Eos, Transactions American Geophysical Union*, 87, 337–343, 2006.

McGillicuddy, D. J., Anderson, L. A., Bates, N. R., Bibby, T., Buesseler, K. O., Carlson, C. A., Davis, C. S., Ewart, C., Falkowski, P. G., and Goldthwait, S. A.: Eddy/wind interactions stimulate extraordinary mid-ocean plankton blooms, *Science*, 316, 1021–1026, 2007.

600 Pauly, D., Trites, A., Capuli, E., and Christensen, V.: Diet composition and trophic levels of marine mammals, *ICES Journal of Marine Science: Journal du Conseil*, 55, 467–481, 1998.

Petrenko, D., Pozdnyakov, D., Johannessen, J., Counillon, F., and Sychov, V.: Satellite-derived multi-year trend in primary production in the Arctic Ocean, *International Journal of Remote Sensing*, 34, 3903–3937, 2013.

Platt, T., Bird, D. F., and Sathyendranath, S.: Critical depth and marine primary production, *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 246, 205–217, 1991.

605 Platt, T., Fuentes-Yaco, C., and Frank, K. T.: Marine ecology: Spring algal bloom and larval fish survival, *Nature*, 423, 398–399, 2003.

Platt, T., Sathyendranath, S., White, G., Fuentes-Yaco, C., Zhai, L., Devred, E., and Tang, C.: Diagnostic Properties of Phytoplankton Time Series from Remote Sensing, *Estuaries and Coasts*, 33, 428–439, 2010.

610 Racault, M.-F., Le Quéré, C., Buitenhuis, E., Sathyendranath, S., and Platt, T.: Phytoplankton phenology in the global ocean, *Ecological Indicators*, 14, 152–163, 2012.

Rolinski, S., Horn, H., Petzoldt, T., and Paul, L.: Identifying cardinal dates in phytoplankton time series to enable the analysis of long-term trends, *Oecologia*, 153, 997–1008, 2007.

Sakov, P., Counillon, F., Bertino, L., Lisæter, K. A., Oke, P. R., and Koralev, A.: TOPAZ4: an ocean-sea ice 615 data assimilation system for the North Atlantic and Arctic, *Ocean Science*, 8, 633–656, doi:10.5194/os-8-633-2012, <http://www.ocean-sci.net/8/633/2012/>, 2012.

Sasaoka, K., Chiba, S., and Saino, T.: Climatic forcing and phytoplankton phenology over the subarctic North Pacific from 1998 to 2006, as observed from ocean color data, *Geophysical Research Letters*, 38, L15 609, doi:10.1029/2011GL048299, 2011.

620 Sathyendranath, S., Cota, G., Stuart, V., Maass, H., and Platt, T.: Remote sensing of phytoplankton pigments: A comparison of empirical and theoretical approaches, *International Journal of Remote Sensing*, 22, 249–273, 2001.

Sharples, J., Ross, O., Scott, B., Greenstreet, S., and Fraser, H.: Inter-annual variability in the timing of stratification and the spring bloom in the North-western North Sea, *Continental Shelf Research*, 26, 733–751, 625 2006.

Siegel, D. A., Doney, S. C., and Yoder, J. A.: The North Atlantic Spring Phytoplankton Bloom and Sverdrup's Critical Depth Hypothesis, *Science*, 296, 730–733, 2002.

Simpson, J., Crisp, D., and Hearn, C.: The shelf-sea fronts: Implications of their existence and behaviour [and discussion], *Philosophical Transactions of the Royal Society of London. Series A, Mathematical and Physical Sciences*, 302, 531–546, 1981.

630 Sverdrup, H. U.: On Conditions for the Vernal Blooming of Phytoplankton, *Journal du Conseil*, 18, 287–295, 1953.

Taboada, F. G. and Anadón, R.: Seasonality of North Atlantic phytoplankton from space: impact of environmental forcing on a changing phenology (1998–2012), *Global change biology*, 20, 698–712, 2014.

635 Taylor, J. R. and Ferrari, R.: Shutdown of turbulent convection as a new criterion for the onset of spring phytoplankton blooms, *Limnology and oceanography*, 56, 2293–2307, 2011a.

Taylor, J. R. and Ferrari, R.: Ocean fronts trigger high latitude phytoplankton blooms, *Geophysical Research Letters*, 38, L23 601, doi:10.1029/2011GL049312, 2011b.

Townsend, D. W., Keller, M. D., Sieracki, M. E., and Ackleson, S. G.: Spring phytoplankton blooms in the 640 absence of vertical water column stratification, *Nature*, 360, 59–62, 1992.

Townsend, D. W., Cammen, L. M., Holligan, P. M., Campbell, D. E., and Pettigrew, N. R.: Causes and consequences of variability in the timing of spring phytoplankton blooms, Deep Sea Research Part I: Oceanographic Research Papers, 41, 747–765, 1994.

Trenkel, V., Huse, G., MacKenzie, B., Alvarez, P., Arrizabalaga, H., Castonguay, M., Goñi, N., Grégoire, F.,
645 Hátún, H., and Jansen, T.: Comparative ecology of widely distributed pelagic fish species in the North Atlantic: implications for modelling climate and fisheries impacts, Progress in Oceanography, 129, 219–243, doi:10.1016/j.pocean.2014.04.030, 2014.

Wiltshire, K., Malzahn, A., Wirtz, K., Greve, W., Janisch, S., Mangelsdorf, P., Manly, B., and Boersma, M.:
650 Resilience of North Sea phytoplankton spring bloom dynamics: An analysis of long-term data at Helgoland Roads, Limnology and oceanography, 53, 1294–1302, 2008.

Yoder, J. A. and Kennelly, M. A.: Seasonal and ENSO variability in global ocean phytoplankton chlorophyll derived from 4 years of SeaWiFS measurements, Global Biogeochemical Cycles, 17, 1112, doi:10.1029/2002GB001942, 2003.

Yoder, J. A., McClain, C. R., Feldman, G. C., and Esaias, W. E.: Annual cycles of phytoplankton chlorophyll concentrations in the global ocean: A satellite view, Global Biogeochemical Cycles, 7, 181–193, 1993.
655

Table 1. Models to explain the Rate of change Phenology Anomaly (R) were built based on published theories regarding the bloom onset. These are indicators of physical processes observed in the North Atlantic.

Name	Parameters	Mathematical expression	References
Critical depth	L_H : light intensity (L) integrated from the surface to the mixed layer depth (H)	$R \sim \alpha_1 L'_H + \beta_1$	Sverdrup (1953); Siegel et al. (2002)
Critical turbulence	Q : heat flux. M : wind-driven mixing	$R \sim \alpha_{2a} Q' + \alpha_{2b} M' + \beta_2$	Huisman et al. (1999); Huisman and Sommeijer (2002); Huisman et al. (2002)
Critical light exposure	L : light intensity. M : wind-driven mixing	$R \sim \alpha_{3a} L' + \alpha_{3b} M' + \beta_3$	Townsend et al. (1994)
Critical heat flux	Q : heat flux. M : wind-driven mixing	$R \sim \alpha_{3a} Q'_0 + \alpha_{3b} M' + \beta_3$	Taylor and Ferrari (2011a, b)

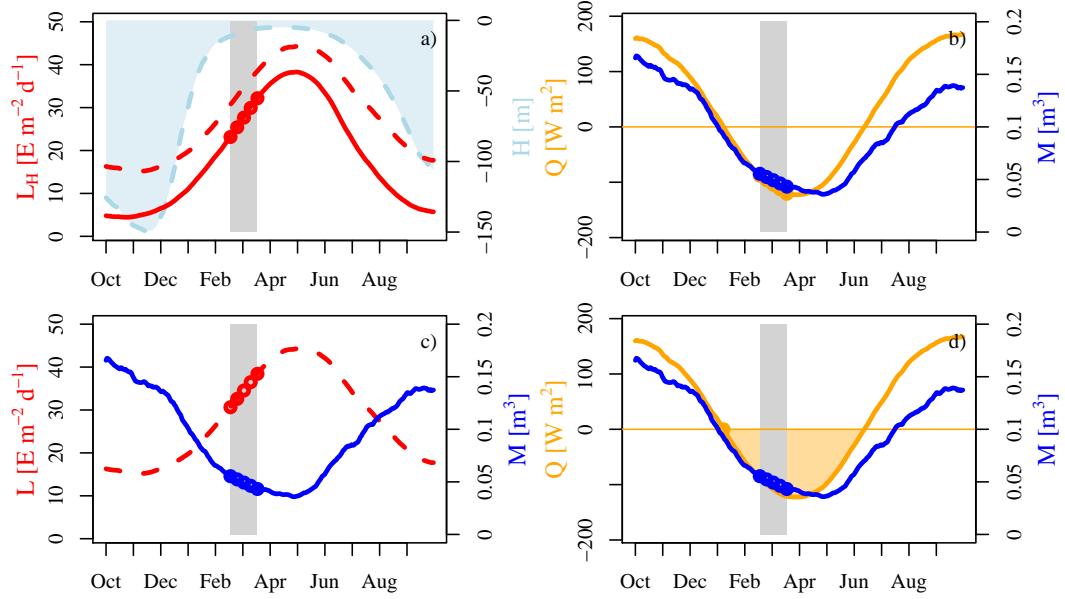


Figure 1. Definitions of each mechanism: a) critical depth; b) critical turbulence; c) critical light exposure; d) critical heat flux (Table 1). Grey vertical area: 30 days prior to the date of climatological maximum rate of change in chlorophyll concentration; open circles: average conditions during the 30 days. Lines show: mixed layer depth (H , light blue), photosynthetic active radiation (L , dashed red), integrated light over the mixed layer depth (L_H , filled red), heat flux (Q , orange), and wind-driven mixing (M , dark blue).

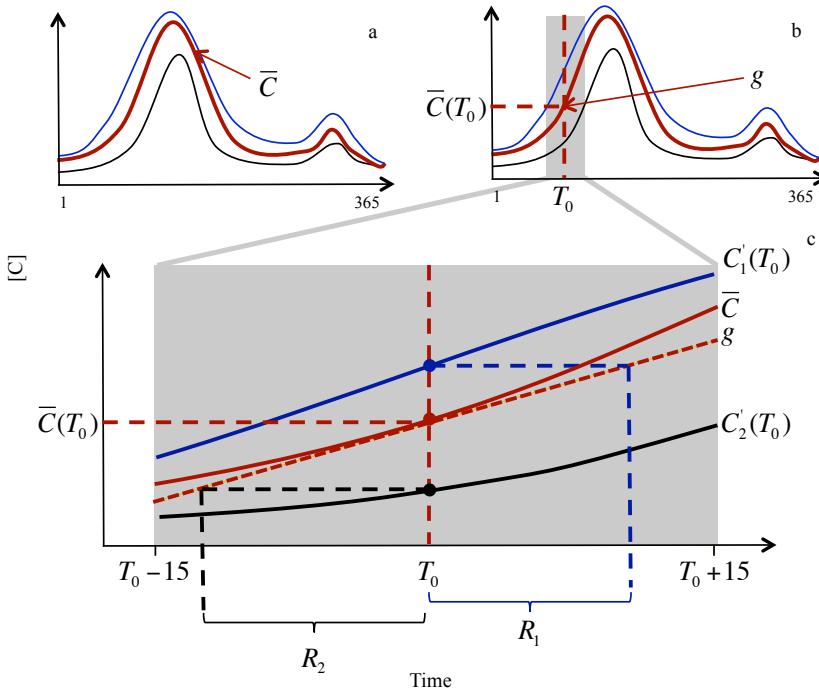


Figure 2. Calculation of the rate of change phenology anomaly for each location x, y , i.e. each $1/4^\circ$ pixel, ($R_i(x, y)$). (a) Each seasonal cycle (dashed, black and blue lines) is used to estimate the climatology ($\bar{C}(x, y, t)$, darkred line). (b) The maximum increase g in \bar{C} and the day on which it occurs (T_0) are used as a reference to estimate how delayed or advanced each year surface bloom is. (c) A 30-day window around the T_0 is isolated for each year seasonal cycle. $R_i(x, y)$ is estimated from the difference between annual $C'_i(T_0)$ and climatology $\bar{C}(T_0)$ and g . The $R_i(x, y)$ is thus a value in days.

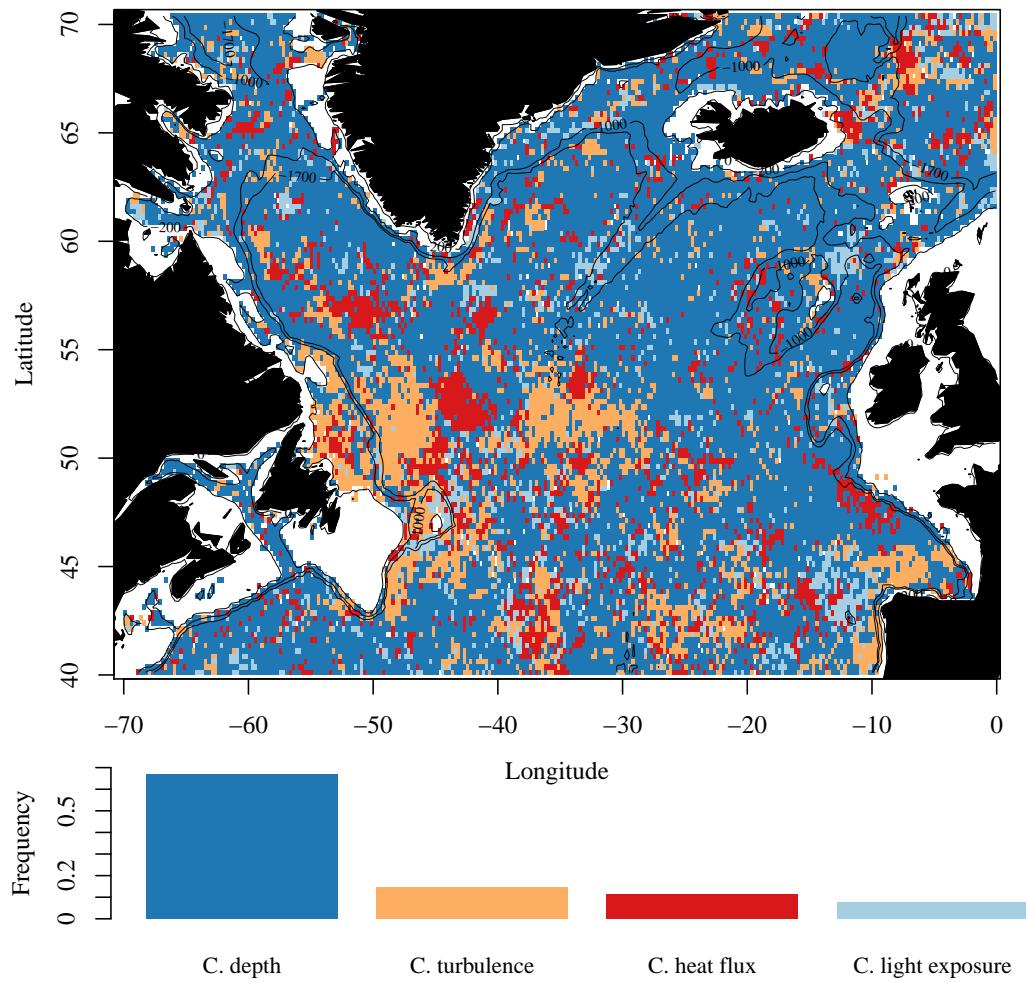


Figure 3. Selected model for each $1/4^\circ$ pixel (top), and relative frequency of each model (bottom). C. depth: critical depth; C. turbulence: critical turbulence; C. light exposure critical light exposure; C. heat flux: critical heat flux. Only pixels where the weight of the winning model is higher than 30 %, and the bottom depth exceeds 200 m are used in this map.

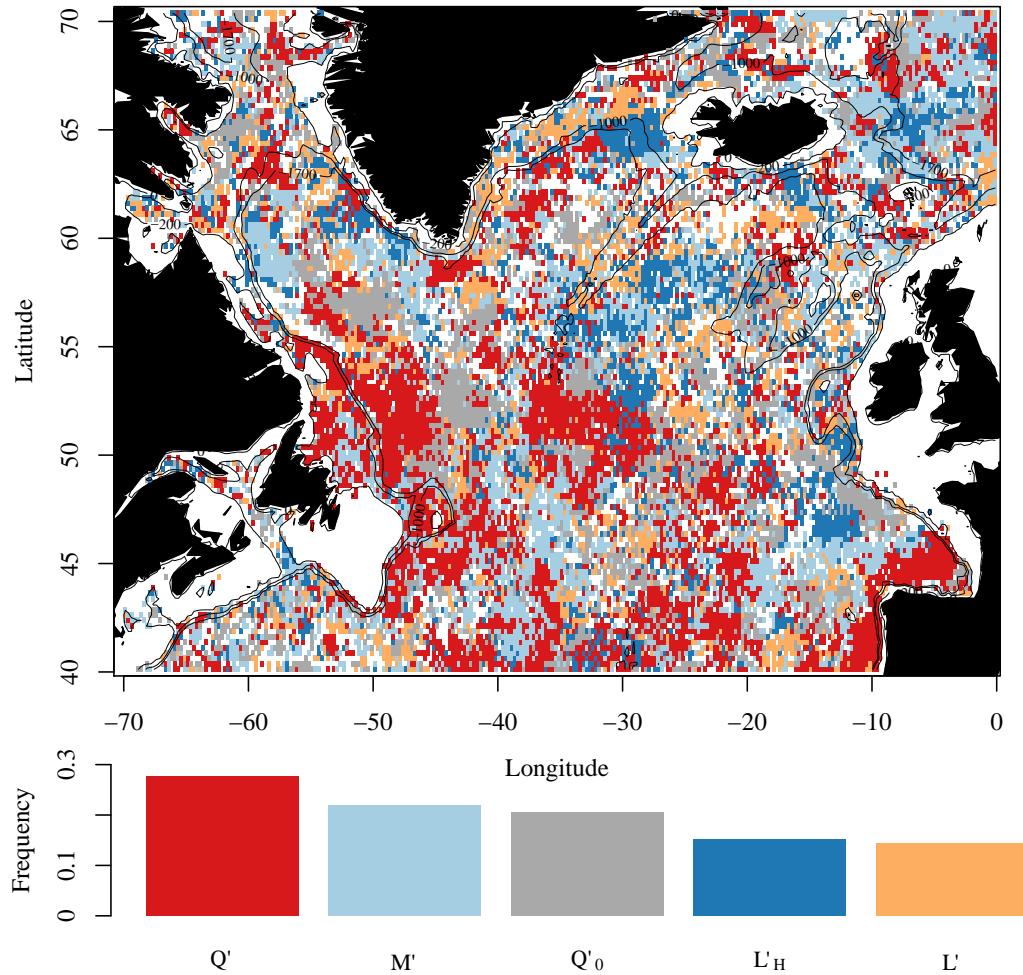


Figure 4. Selected variable for each $1/4^\circ$ pixel (top), and relative frequency of each single-variable model (bottom). PAR integrated to the MLD: L'_H ; PAR: L' ; wind-driven mixing: M' ; heat flux: Q' and start of net warming: Q'_0 . Only pixels where the weight of the winner model is higher than 30 %, and the bottom depth exceeds 200 m are used in this map.

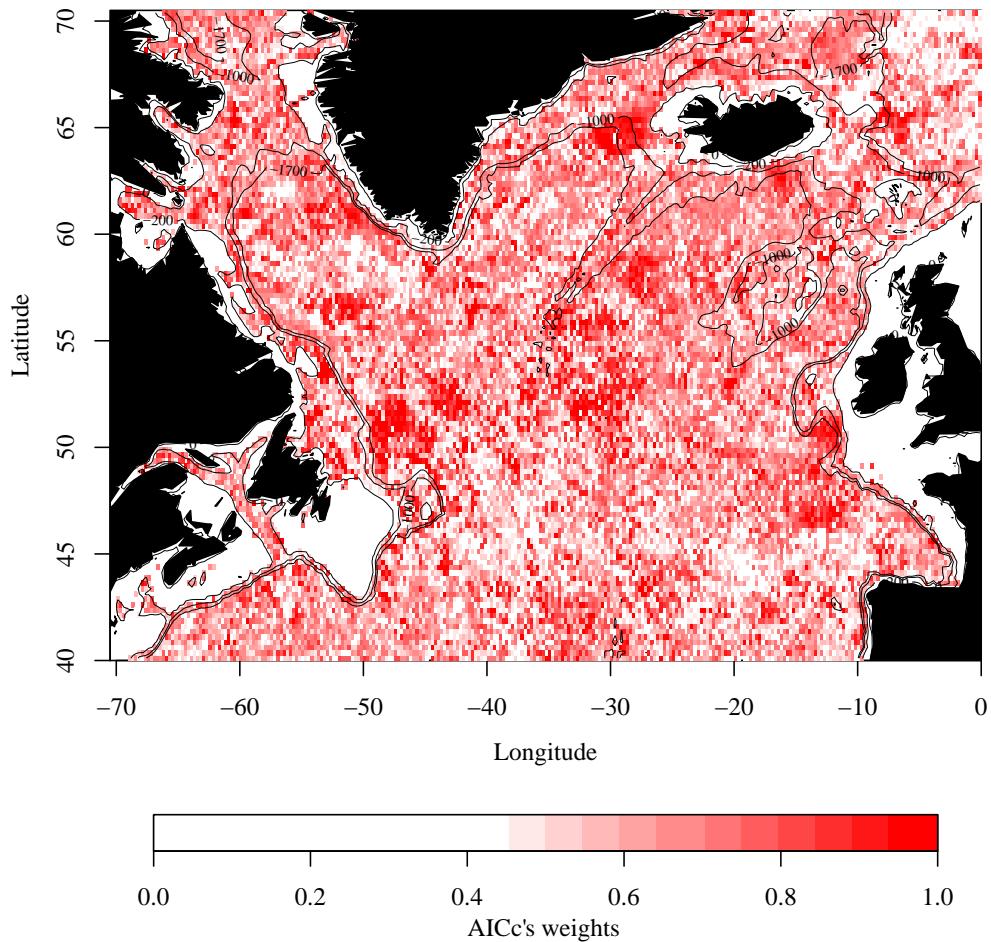


Figure A 1. Akaike weights of the selected model for each $1/4^\circ$ pixel as in Figure 3 in the main manuscript. Only pixels where the weight of the winner model is higher than 30 %, and the bottom depth exceeds 200 m are used in this map.