1 Observed global ocean phytoplankton phenology indices.

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13 Abstract

14 Phytoplankton bloom phenology is an important indicator for the monitoring and management of marine resources 15 and the assessment of climate change impacts on ocean ecosystems. Despite its relevance, there is no long-term 16 and sustained observational phytoplankton phenological product available for global ocean implementation. This 17 need is addressed here by providing a phenological data product (including among other seasonal metrics, the 18 bloom initiation, termination, duration, and amplitude timing) using satellite derived chlorophyll-a data from the 19 Ocean Colour Climate Change Initiative. This multi-decadal data product provides the phenology output from 20 three widely used bloom detection methods at three different spatial resolutions (4, 9 and 25 km) allowing for 21 both regional and global-scale applications. When compared to each other on global scales, there is general 22 agreement between the detection methods and between the different resolutions. Regional differences are evident 23 in coastal domains (particularly for different resolutions) and in regions with strong transitions (notably for 24 different detection methods). This product can be used towards the development of national and global 25 biodiversity assessments, pelagic ecosystem mapping and for monitoring change in climate sensitive regions relevant for ecosystem services. The dataset is published in the Zenodo repository under the following DOIs, 4 26 27 km: <u>https://doi.org/10.5281/zenodo.8402932</u>, 9 km: <u>https://doi.org/10.5281/zenodo.8402847</u> and 25 km: https://doi.org/10.5281/zenodo.8402823 (Nicholson et al., 2023a, b, c) and will be updated on annual basis. 28

29 1 Introduction

30 The seasonal proliferation of phytoplankton across the world's ocean is a ubiquitous signal visible from space, 31 and one that plays a crucial role in the Earth system. Phytoplankton "blooms" capture 30-50 billion metric tons of 32 carbon annually, representing almost half of the total carbon uptake by all plant matter (Buitenhuis et al., 2013; 33 Carr et al., 2006; Falkowski, 1994; Field et al., 1998; Longhurst et al., 1995). Their key role in driving the strength 34 and efficiency of the biological carbon pump, the transfer of atmospheric carbon to the deep ocean interior, is a 35 crucial component of the global carbon cycle and instrumental in the assessment of climate feedbacks and change 36 (DeVries, 2022; Henson et al., 2011). Phytoplankton also mediate climate through the production of important 37 atmospheric trace gases such as nitrous oxide, a potent greenhouse gas, and volatile organic carbons such as 38 dimethyl sulphide, that have a significant impact on cloud formation and global albedo (Charlson et al., 1987; 39 Korhonen et al., 2008; McCoy et al., 2015; Park et al., 2021). As the foundation of the marine food chain, 40 phytoplankton are critical to supporting higher trophic levels and a lucrative fisheries industry that impacts global 41 food security (Gittings et al., 2021; Stock et al., 2017). There is an enormous benefit to society in being able to 42 predict ecosystem responses to environmental change, by providing the knowledge necessary for competent 43 decision-making. As such understanding, characterising and accurately predicting changes in the annual cycle of 44 phytoplankton blooms provides an essential tool for managing marine resources and for predicting future climate 45 change impacts (Thomalla et al., 2023; Tweddle et al., 2018).

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47 Phytoplankton phenology refers to the timing of seasonal activities of phytoplankton biomass and is used widely 48 as an indicator to characterise phytoplankton blooms and to monitor their variability over time. Adjustments in 49 the characteristics of phenology typically reflect alterations in ecosystem function that may be linked to 50 environmental pressures such as climate change (Henson et al., 2018; Racault et al., 2012; Thomalla et al., 2023). 51 Key phenological phases of phytoplankton bloom development include: the time of initiation, the time of 52 maximum concentration (amplitude), the time of termination and duration as the time between initiation and 53 termination. These phytoplankton bloom phases are typically driven by seasonal changes in physical forcing (such 54 as incoming solar radiation, water column mixing and nutrient depletion), which are generally linked to large-55 scale climate drivers (Racault et al., 2012; Thomalla et al., 2023). The timing of the bloom initiation and amplitude 56 is particularly critical for efficient trophic energy transfer, which can be impacted negatively through trophic 57 decoupling. For example, mismatches between bloom timing and zooplankton grazing can lead to suboptimal 58 food conditions for higher trophic levels which in turn has been linked to the collapse of crucial fisheries (Cushing, 59 1990; Koeller et al., 2009; Seyboth et al., 2016; Stock et al., 2017). Bloom duration impacts the amount of biomass 60 being generated within a season that can be exported to the ocean's interior or transferred to higher trophic levels 61 via the marine food web and can thus play a more important role than bloom magnitude (Barnes, 2018; Rogers et 62 al., 2019). Bloom timing has also been shown to influence the seasonal cycles of CO₂ uptake, primary production 63 and the efficiency of carbon export and storage (Bennington et al., 2009; Boot et al., 2023; Lutz et al., 2007; 64 Palevsky and Quay, 2017) Having access to a global data product that characterises the seasonal cycle of 65 phytoplankton over the last 25 years and into the future can thus provide a valuable tool to users that require an

66 understanding of key aspects of the growing season and how these may be changing over time.

Current generation Earth System Models (ESMs) show that phytoplankton phenology is changing and will 67 68 continue to change in response to a warming and more stratified ocean (Henson et al., 2018; Yamaguchi et al., 69 2022). For example, blooms are predicted to initiate later in the mid-latitudes and earlier at high and low latitudes 70 by \sim 5 days per decade by the end of the century (Henson et al., 2018). But what about changes in bloom phenology 71 in the contemporary period? Satellite-based ocean colour remote sensing, which provides estimates of 72 chlorophyll-a (chl-a) concentrations (a proxy for phytoplankton abundance), is the only observational capability 73 that can provide synoptic views of upper ocean phytoplankton characteristics at high spatial and temporal 74 resolution (~1 km, ~daily) and high temporal extent (global scales, for years to decades). In many cases, these are 75 the only systematic observations available for chronically under-sampled marine systems such as the polar oceans. 76 In 1997, the first global ocean colour observing satellite (SeaWiFS) was launched and these observations have 77 been sustained through a successive series of additional ocean colour satellites (MODIS, MERIS, VIIRS, OLCI). 78 These have all been merged by the European Space Agency into the Ocean Colour Climate Change Initiative 79 (OC-CCI) remotely-sensed observational data product, which provides ~25 years of ocean colour data for climate 80 change assessment (Sathyendranath et al., 2019). We note however that despite their obvious spatial and temporal 81 advantages, remotely detected water-leaving radiances emanate from only the first optical depth, and give little 82 quantitative information about the vertical structure of the water column, which can be particularly important in 83 low nutrient regions where a subsurface chl-a maxima is prevalent. In addition, we recognise that the OC-CCI 84 chl-a observational data product may exhibit regional biases (that can vary in both magnitude and direction) and 85 arise from several factors inherent to both satellite remote sensing technology and the complexities of ocean 86 ecosystems. One example is that algorithms are often regionally trained on datasets from specific parts of the 87 world, which can result in discrepancies when applied globally. Despite these regional biases, satellite ocean 88 colour chl-a observational data products remain highly valuable, especially when the goal is to identify patterns 89 in the seasonal cycle of phytoplankton and how these patterns evolve over time. While local accuracy may be 90 impacted by biases, the broader trends—such as the timing of spring blooms, the intensity of summer productivity, 91 or the length of growing season-are still well captured. This is because biases tend to be relatively consistent 92 over time in any given region, allowing researchers to focus on changes in these patterns rather than on the absolute 93 values. These long-term changes in the seasonal cycle are crucial for understanding how marine ecosystems 94 respond to environmental stressors like warming temperatures, ocean acidification, and changes in nutrient 95 availability.

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97 The estimation of phytoplankton phenology from OC-CCI remote sensing of chl-a can provide important 98 information of the rates of change in key indices on a global scale for comparison to those derived from ESM's. 99 For example, a recent study by Thomalla et al., (2023) determined the trends in phenology metrics in the Southern 100 Ocean using 25 years of satellite-derived chl-a (1997-2022) data. Their results revealed that large regions of the 101 Southern Ocean expressed significant trends in phenological indices that were typically much larger (e.g. <50 102 days decade⁻¹) than those reported in previous climate modelling studies ($\leq 5-10$ days decade⁻¹), which suggests 103 that ESM's may be underestimating ongoing environmental change. Thomalla et al., (2023) conclude, that 104 seasonal adjustments of this magnitude at the base of the food web may impact the nutritional stress, reproductive 105 success, and survival rates of larger marine species (e.g., seals, seabirds, and humpback whales), in particular if

106 they are unable to synchronise their feeding and breeding patterns with that of their food supplies. It is anticipated

107 that a similar analysis using these key phytoplankton metrics applied to the global ocean or specific regions of 108 interest will reveal regional sensitivities of ecosystems to change with important implications for ecosystem 109 function and associated societal impacts. There is also a need for the continuous monitoring and ongoing 110 assessment of the seasonal adjustments of phytoplankton on global scales (in addition to continued benchmarking 111 for ESMs), which would require regular updates of key phenological metrics going forward. Such information is 112 relevant for effective marine management programs and early detection of vulnerabilities in key regions, e.g., 113 those necessary for sustaining fisheries. In addition, a phenology data product such as this can provide a useful 114 aid for the planning of oceanographic research campaigns that wish to align with or determine their occupation 115 relative to key aspects of the growing season. Finally, this data product could also be valuable to support those 116 users without the programming know-how or access to computationally expensive resources that are required to 117 generate it.

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Here we present a new global phytoplankton phenological data product with indicators that include among other metrics bloom initiation, termination, amplitude, and duration. These metrics are computed using three different gridded resolutions (4, 9 and 25 km) and with three different methodologies of determining phenology. This derived observational data product facilitates the global characterisation of the climatological seasonal cycle and can be used to identify the sensitivity of the seasonal cycle to change (through the analysis of trends and anomalies). The phenology data product is currently available from 1997 until 2022 and will be updated annually and in sync with any version updates of the OC-CCI chl-a observational data product.

126 2 Methodology

127 **2.1 Data and pre-processing**

128 Satellite-derived chl-a concentrations (mg m⁻³) were obtained from the European Space Agency (ESA), from OC-129 CCI (https://esa-oceancolour-cci.org; (Sathyendranath et al., 2019) at 4 km and 8-day resolution. The latest 130 available OC-CCI product (version v6.0, released on 04/11/2022) is used in this present study. This version marks 131 a substantial change to previous versions (e.g., v5.0, see Sathyendranath et al., (2021)) in that it incorporates Sentinel 3B OLCI data, the MERIS-4th reprocessing dataset, upgraded Quasi-Analytical algorithm (QAAv6) and 132 133 the exclusion of MODIS and VIIRS data after 2019 (refer to D4.2 - Product User Guide for v6.0 Dataset from https://climate.esa.int/en/projects/ocean-colour/key-documents/ for further details on processing and validation). 134 135 The OC-CCI observational data product was generated with the specific aim of studying phytoplankton dynamics 136 at seasonal to interannual scales. Indeed, it has been used widely by the scientific community for studying 137 phytoplankton phenology (e.g., Anjaneyan et al., 2023; Delgado et al., 2023; Ferreira et al., 2021; Gittings et al., 138 2019, 2021; Racault et al., 2017; Silva et al., 2021; Thomalla et al., 2015, 2023). Data provided by OC-CCI 139 covered the period from 29/08/1997 - 27/12/2022 for the global ocean ($90^{\circ}N - 90^{\circ}S$ and $180^{\circ}E - 180^{\circ}W$). 140

141 The phenological indices described below are calculated using three horizontal resolutions in surface chl-a, the 142 native 4 km resolution as provided by OC-CCI and a regridded 9 km and 25 km horizontal resolution. The 4 km

143 and 9 km resolutions are considered important for smaller-scale regional needs such as coastal applications and 144 field campaigns. The 25 km resolution is the most computationally efficient for users to work with, it results in a 145 reduction of missing data and is useful for global open-ocean applications. For the 9 km and 25 km resolutions, 146 chl-a is regridded onto a regular grid through bilinear interpolation using the xESMF Python package (Zhuang et 147 al., 2023). In all resolutions for phenological detection, data gaps were reduced further by applying a linear 148 interpolation scheme in sequential steps of longitude, latitude, and time (Racault et al., 2014). A two-point limit 149 (e.g., the maximum number of consecutive empty grid cells to fill) is chosen for the interpolation to avoid 150 overfilling of regions that contain larger coherent data gaps. We further apply a 3 time-step (24 days) rolling mean 151 along the time dimension to avoid any outliers that may result in fake detection points. However, for the Seasonal 152 Cycle Reproducibility (SCR) computations only interpolation (time, lat and lon) is carried out, this is discussed

153 further below.

154 **2.2 Phenological Indices and Detection**

155 Phytoplankton blooms typically manifest as a seasonal cycle, with a bloom initiation that identifies the timing of the ramp up in phytoplankton growth and biomass accumulation followed by bloom peaks within the growing 156 157 season (which could be multiple) and finally the bloom termination, which defines the end of the growing season. The phenological indices applied here are based on those applied to the SO in Thomalla et al. (2023). To calculate 158 159 the phenological indices for initiation and termination, we apply three main detection methods used by the 160 community (e.g. Brody et al., 2013; Ji et al., 2010), which are detailed below (iii and iv). Each detection method 161 has its strengths and weaknesses, and therefore the choice of method for application can be determined by the user 162 needs, which are elaborated on in Brody et al. (2013). These methods were chosen over other approaches (e.g. 163 Platt et al., 2009; Rolinski et al., 2007) due to the method's suitability for estimates across global scales as it is 164 capable of encompassing a wide range of different shapes in phytoplankton blooms (Racault et al., 2012). In this 165 derived observational data product, all three approaches are provided globally at all three resolutions. Below we 166 outline the series of steps implemented for estimating the global phenological indices and provide an 167 accompanying flow chart (Figure 1) to illustrate the succession of steps being implemented. In addition, we 168 provide some example applications at four key observing stations (Figure A1) to facilitate a visualisation of the derived phenological indices from four annual time series. 169

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171 (i) Bloom maximum climatology: The climatological peak (maximum amplitude) of the bloom was identified as 172 the local maximum in chl-a occurring within each grid cell's 25-year climatology. This approach was necessary 173 because the timing of bloom events varies globally, i.e., southern hemisphere blooms typically occur during austral 174 spring - summer (September - February), while northern hemisphere blooms occur in boreal spring - summer 175 (April - August) (Racault et al., 2012). Furthermore, both hemisphere tropics tend to be approximately 6 months out of phase with both hemisphere higher latitude regions. As such, it would be inappropriate to use a fixed date 176 177 period (or "bloom slice" see below) to identify bloom occurrence on global scales. Instead, for each grid cell we calculate the 8-day mean climatology. The date of the maximum climatological bloom for each pixel is then used 178 179 to centre the timing of the phenology detection methods described below.

181 (ii) Identification of bloom peaks: For every pixel on a year-by-year basis we take the climatological bloom

- 182 maximum peak ± 6 months and determine the date and magnitude of the bloom maximum peak for each year. To
- ensure that seasonal blooms with more than one peak could be accounted for, multiple bloom peaks were defined
- as a second, third, or n^{th} local maxima where the chl-a concentration reached at least 75% of the amplitude of the
- bloom maximum peak magnitude and were a minimum of 24 days (i.e., 3 x 8 day time intervals) away from the bloom maximum peak for that year. The 75% threshold was chosen to identify peaks with similar magnitude to
- 187 the bloom maximum peak so as to allow for the occurrence of a multiple peak growing season. Choosing a
- 188 threshold higher than this would likely exclude recognisable bloom peaks (which could lead to an underestimate
- 189 of the bloom duration), while choosing a lower threshold may include sub-seasonal variability and lead to an
- 190 overestimation of the bloom duration. These additional peaks were found within ± 6 months of the maximum peak.
- 191 An example of such a multi-peak bloom detection is provided in Figure 1 and Figure A1c. The additional peaks
- 192 were identified with the Python SciPy (Virtanen et al., 2020) function 'find peaks'.
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(iii) The 'bloom slice': The bloom slice, used to find the bloom initiation and termination dates, is identified for
each pixel as the 6-month time span preceding and following from the maximum bloom peak (ii). Or in the case
of multi-modal blooms, 6-months preceding the first and following the last peak respectively.

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(iv) Bloom initiation: The bloom initiation date for each bloom slice as described in (iii) is calculated as the first
date before either the bloom maximum, or the first peak in the event of multi-modal blooms, according to the
following thresholds:

- Biomass-based threshold method (TS): First determine the range as the difference in chl-a concentration
 between the bloom maximum and preceding minimum. Then identify the bloom initiation as the first
 date that the chl-a concentration was greater than the minimum chl-a concentration plus 5% of the chl-a
 range.
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 2. *Cumulative biomass-based threshold method (CS):* First remove any values preceding the bloom slice
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- 3. *The rate of change method (RC):* First determine the rate of change of the bloom slice and then identify
 the first date that the chl-a rate of change was greater than 15% of the median rate of change in chl-a
 concentration.
- To note, the choice of above chosen percentage thresholds are in accordance with those used by previous phenological detection studies (Brody et al., 2013; Henson et al., 2018; Hopkins et al., 2015; Ji et al., 2010; Thomalla et al., 2011, 2015, 2023).
- 215 (v) Bloom termination: The bloom termination date for each bloom slice was similarly calculated as the first date
- 216 after the bloom maximum, or the last peak in the event of multi-modal blooms, according to the following 217 thresholds:
- *TS*: the first date that the chl-a concentration was less than the minimum chl-a concentration plus 5% of
 the chl-a range.

220 2. *CS:* the first date that the chl-a concentration was less than 15% of the total cumulative chl-a 221 concentration.

RC: the first date that chl-a rate of change was less than 15% of the median rate of change in chl-a concentration.(vi) Bloom duration: The bloom duration was calculated as the number of days between the bloom initiation and termination dates. This is applied to each phenological detection method described above (TS, CS and RC).

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(vii) Integrated and mean bloom chl-a: The seasonally integrated bloom chl-a was calculated using the NumPy
 (Harris et al., 2020) trapezoidal function as the chl-a concentration integrated between the bloom initiation and
 termination dates. The seasonal mean chl-a was calculated as the average chl-a between the bloom initiation and
 termination dates. These are applied to each of the three phenological detection methods described above (TS, CS
 and RC).

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233 (viii) SCR: The variance of the seasonal cycle was calculated as defined in Thomalla et al., (2023), where the SCR 234 is the Pearson's correlation coefficient of the annual seasonal cycle correlated against the climatological mean 235 seasonal cycle. A value of 100% is indicative of an annual seasonal cycle that is a perfect repetition of the 236 climatological mean, while a value of 0% means that there is no annually reproducible mean seasonal cycle. Unlike for phenological indices i-vii, for SCR the original OC-CCI v6.0 data were used for the three different grid 237 238 resolutions, however with only spatial-temporal interpolation for gap filling and no rolling mean to avoid 239 smoothing out temporal variability. For SCR for each pixel the bloom slice is restricted to 12 months (i.e., January 240 to December).

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The cyclical nature of the year day calendar presents a significant challenge when calculating means and standard deviations of phenological indices. For example, we need to avoid a situation where the mean bloom initiation between a year with a bloom in December (day of year = 340) and a year with a bloom in January (day of year = 10) is incorrectly calculated as an average bloom initiation date in July (day of year = 175). To address this, as similarly applied in Thomalla et al. 2023, we used the Python SciPy function circmean (or circstd for standard deviation), which calculates circular means for samples within a specified range, correctly identifying the mean as day of year 357.



252 Figure 1: Methodological flow chart outlining the steps taken to calculate the phytoplankton seasonal metrics. An 253 example time-series illustrating the performance of the resulting phenological indices for a bimodal (double peak) 254 bloom in the Southern Ocean (45°S, 7.5°W) is provided for the three different phenological methods, biomass-255 based threshold (TS), cumulative sum (CS) and rate of change (RC). *See Methodology for pre-processing steps.

256 **3** Results and Discussion

257 3.1 Global open-ocean phytoplankton seasonal metrics

258 A significant degree of regional variability is evident in the mean distribution of seasonal metrics (bloom 259 amplitude, timing, and seasonality) (Figure 2). Bloom magnitude metrics (max bloom chl-a, mean bloom chl-a 260 and integrated bloom chl-a; Figure 2a-c) are all higher in the high-latitudes and in the coastal regions, particularly 261 in the Eastern Boundary Current Systems, and lowest in the oligotrophic subtropical gyres. There is a general

equator-to-pole symmetry in the timing of phytoplankton blooms between the northern and southern hemispheres. 262 263 In the subpolar regions phytoplankton blooms initiate in the northern hemisphere during Boreal Spring to early 264 summer (March-May) and in the southern hemisphere in Austral Spring to early summer (September-November) 265 in response to light availability (Sverdrup, 1953) (Figure 2d). While in the subtropics, where there is ample light 266 throughout the year, blooms typically initiate in autumn to winter in response to nutrient supplies through winter-267 driven deepening of the mixed-layer (Fauchereau et al., 2011; Thomalla et al., 2011). In both the Antarctic and 268 Arctic polar regions, phytoplankton blooms initiate in Austral (December) and Boreal summer (July), when the sea-ice cover melts. The timing of bloom maximum follows the same equator-to-pole symmetry as bloom 269 270 initiation (Figure 2g), with high latitude regions peaking in Austral and Boreal summer, whereas the subtropics 271 peak in Austral and Boreal winter. This large-scale meridional structuring of the bloom timing is as expected and 272 similarly found in previous large-scale satellite based phenological studies (Kahru et al., 2011; Racault et al., 273 2012: Sapiano et al., 2012). There is a larger degree of spatial heterogeneity in bloom termination (Figure 2e). 274 particularly evident in regions such as the high latitude North Atlantic and sub-Antarctic, with terminations that 275 extend up to 6 months later in comparison to surrounding areas which were initiated at a similar time. This 276 manifests in zonal asymmetries across the different basins for bloom duration (Figure 2f), with considerably 277 longer blooms occurring in the Pacific basin compared with the Atlantic and Indian basins. SCR covers a large 278 range of variability across latitudinal bands. Notably, SCR (Figure 2h) is oftentimes low in regions where bloom duration is long, and this relationship is strongest in the tropical Pacific (r \sim -0.4). In the Southern Ocean, long-279 280 sustained but highly variable blooms were proposed as a response to intermittent physical forcing (high-frequency 281 wind and meso to submesoscale dynamics) that entrain nutrients and postpone the seasonal termination (Thomalla 282 et al., 2011).



Figure 2: Global distribution of phytoplankton seasonal metrics. Mean [1998 - 2022] maps of (a) bloom max 284 chlorophyll (chl-a), (b) mean chl-a over bloom duration, (c) integrated chl-a over bloom duration, (d) bloom 285 286 initiation, (e) bloom termination, (f) bloom duration, (g) bloom max chl-a date, and (h) seasonal cycle 287 reproducibility (SCR). Phenological indices (b-f) are determined using the Biomass-based threshold method as 288 defined in Henson et al., 2018; Thomalla et al., 2023.

289 3.2 Comparison between phenology detection methods

290 Phytoplankton blooms can initiate rapidly, slowly, be short lived, intermittent, or sustained over a growing season,

291 with different detection methods being more or less sensitive to these varying characteristics of the seasonal bloom 292 (Brody et al., 2013; Ji et al., 2010; Thomalla et al., 2023). In this derived observational data product we have

293 chosen to provide three widely used bloom detection methods for all three resolutions allowing the user to

294 determine which method (or all) is most appropriate for their region and application (Figure 3 and Figure A2).

- Indeed, these methods each have their strengths and weaknesses. For example, as explained in Brody et al. (2013),
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- the biomass based TS method will likely capture the bloom start dates at the largest increase in chlorophyll 296 297 concentrations. It is thus more suitable for studies wanting to investigate the match or mismatch between

298 phytoplankton and upper trophic levels as the match-mismatch hypothesis is based on the timing of the high 299 phytoplankton biomass period (Cushing, 1990). This method has been found to be relatively insensitive to the percentage of the threshold used (Brody et al., 2013; Siegel et al., 2002). The RC method, which identifies the 300 301 bloom initiation as the time when chl-a increases rapidly, is likely more suitable for investigating the physical or 302 biochemical mechanisms that create conditions in which the bloom occurs (Brody et al., 2013). Whereas the CS 303 method could be used to identify either of the features above, Brody et al. (2013) showed that, while there are 304 sensitivities of the CS method to the threshold chosen, the 15% threshold as applied here, is most appropriate at 305 capturing bloom initiation dates of both subpolar and subtropical regions and thus most appropriate to be applied 306 across global scales. It is interesting and potentially valuable to determine when and where different methods of 307 determination agree or disagree, and we advocate for users to apply all three methods so that they may interrogate 308 the differences and make informed decisions about choosing one over another or utilising all three to define a 309 range in the desired metric. In Figure 3, the standard deviation (STD) between the three methods is applied 310 globally to assess the agreement between climatological means from the different methods.

Across large regions of the global ocean, there is good agreement between the different methodological 311 312 approaches (e.g. the global mean STD for the phenological timing indices is ~8-days) (Figure 3 a- b) All methods 313 produce similar large-scale patterns (Figure A2 a-c, g-f, m-o). There are however some specific regions where 314 larger differences in timing emerge of ~30-50 days (Figure 3 and Figure A2 d-f, j-l), which are of a similar order 315 of magnitude as reported by Brody et al. (2013) who found areas with differences exceeding two months. The 316 largest differences for both bloom initiation and termination tend to coincide with transitional zones such as at 317 the boundaries between the subtropical and subpolar gyres in both hemispheres and in all three basins (Figure 318 3a,b). This is not too surprising, given that these boundaries represent areas of significant biogeochemical 319 signatures and regime shifts between phytoplankton seasonal characteristics with strong north-south gradients in 320 bloom metrics (Figure 2). While there are no other comparisons of these detection methods on a global scale, such 321 differences were similarly seen in Brody et al. (2013) for the North Atlantic bloom, their Figure 4, where the 322 largest differences between bloom initiation methods occurred at the sharp transition boundaries between the 323 subtropical and subpolar latitudes. In general, there is stronger agreement between methods in the higher subpolar latitudes compared to subtropical latitudes, as evidenced by slightly elevated STDs in the subtropical gyres (Figure 324 325 3a,b). The subtropical oligotrophic regions are characterised by phytoplankton seasonal cycles that typically have 326 lower bloom amplitudes, are more gradual and have longer durations (Figure 2). The TS method tends to produce 327 earlier bloom initiations and earlier terminations in these subtropical regions (Figure A2 d-e, j-k). In these regions 328 the chl-a min-max range is relatively small, thus a 5% threshold may be exceeded earlier in both termination and 329 initiation. The RC method, based on the rate of change, is likely to produce later bloom timing dates in more 330 gradual blooms. There is agreement in the resultant bloom durations between the different methods, with similar 331 large-scale patterns being reproduced by all three methods (Figure 3c, Figure A2m-o). Unsurprisingly, in the 332 oligotrophic regions, differences between the methods in bloom duration do not translate to large differences in 333 the integrated and mean bloom chlorophyll because of the low magnitude of the chlorophyll (Figure 2a-c, Figure 334 3 c-e). There are however, corresponding regions with more noteworthy disagreements in both duration and mean 335 and integrated bloom chlorophyll, for example in the energetic regions of the Antarctic Circumpolar Current,

- 336 particularly near sub-Antarctic Islands, and localised coastal regions with significant river runoff, such as in the
- 337 Atlantic where the Amazon River discharge occurs. These areas of large STDs between the methods are driven
- 338 predominantly by the TS method (Figure A2p-r), which tends to result in shorter blooms, due to later initiations

and earlier terminations (Figure A2 d, e, j, k).



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Figure 3: Comparisons between phenological detection methods. Shown are standard deviations (STD)
calculated between the biomass-based threshold method, the cumulative biomass-based threshold method and
the relative of change method , for selected seasonal phytoplankton bloom metrics, including (a) bloom

initiation, (b) bloom termination, (c) bloom duration, (d) bloom integrated chl-a and (e) bloom mean chl-a.

345 **3.3. High-resolution phenology indices**

346 The derived phenology data product presented here is offered at three different horizontal resolutions (4, 9 and 25

347 km), which when compared on a global scale (Figure 4) shows little to no difference in the overall mean

348 distribution of three selected phytoplankton seasonal metrics, including bloom mean chl-a (Figure 4a), bloom

349 duration (Figure 4b) and SCR (Figure 4c). Given that the large-scale distributions of the seasonal metrics remain

350 virtually the same there is little benefit for the user to use the more computationally expensive 4 km product for

351 applications across these larger scales.



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Figure 4: Probability Density Functions (PDF) of climatological mean (calculated from 1998 to 2022) phytoplankton seasonal cycle metrics, compared across three different spatial resolutions (4, 9 and 25 km) for (a) bloom mean chlorophyll-a, (b) bloom duration and (c) seasonal cycle reproducibility (SCR). The TS phenology method is used for (a) and (b).

358 There are, however, notable differences in the resolution of the product on smaller regional scales which appear 359 qualitatively different when compared at two example sites (Figure 5). The sites were selected to reflect regions 360 where a critical dependence is anticipated on the timing and magnitude of seasonal phytoplankton production. 361 The Benguela upwelling system (Figure 5a-c), off the west coast of South Africa is an essential region for 362 supporting key fisheries, while the subAntarctic Kerguelen Island (Figure 5d-f) is a vulnerable marine ecosystem 363 that supports a number of key species. The coarseness of the 25 km product is clearly evident in both sites at these 364 scales, it is considerably more pixelated and there are notable patches where there are differences in the resultant phenological metric between resolutions. For example, in the near-shore of St Helena Bay the integrated bloom 365 366 chl-a climatology (2017-2022) differs between resolutions from 1654 mg m-3 bloom-1, 1841 mg m-3 bloom-1, and 1843 mg m-3 bloom-1, for the 25 km, 9 km and 4 km maps respectively. At Kerguelen Island, interaction of 367 368 the Polar Front with shallow bathymetry generates persistent fine-scale ocean dynamics that set strong regional gradients in phytoplankton production (Park et al., 2014). These fine-scale gradients are clearly seen in the spatial 369 370 variability of bloom duration captured by the higher resolution products. The 'footprint' of the island is evident 371 in the extended bloom durations occurring over the shallow plateau associated with the island where there is 372 considerable resuspension of dissolved iron, a key limiting nutrient (Blain et al., 2001). These examples highlight 373 how this data product can be applied to derive valuable indicators for use in national biodiversity assessments, 374 pelagic ecosystems mapping and marine resource management with the added potential of monitoring change in 375 climate sensitive regions relevant for ecosystem services. For regional studies or applications in coastal domains it is recommended that users favour the high spatial resolution product, as it could facilitate detection of finer 376 377 scale delineations of phenoregions in transitional waters or detect fine scale distributions in phenology metrics 378 that are associated with physical or oceanographic features such as eddies, bays, and upwelling cells. While some 379 phenology indicators produced from daily data could offer additional insights into coastal regions with high 380 temporal variability (e.g., Ferreira et al., 2021), our dataset offers a resource for areas where long gaps in the time-381 series could negate the use of daily data. 382



383

Figure 5: Regional domains comparing the impact of different resolutions (a,d) 25 km, (b,e) 9 km and (c,f) 4 km on (a-c) bloom integrated chl-a and (d-f) the bloom duration averaged from 2017-2022 for (a-c) the Benguela upwelling system off the west coast of South Africa and (d-f) Kerguelen, a subAntarctic island in the Southern

387 Ocean.

388 4 Data availability

The data are available on the Zenodo repository under the following DOIs, 4 km: 10.5281/zenodo.8402932, 9 km:
10.5281/zenodo.8402847 and 25 km: 10.5281/zenodo.8402823 (Nicholson et al., 2023a, b, c). Chl-a data, used to
develop the phytoplankton phenology product, is available from the Ocean Colour–CCI dataset (v.6.0) at
https://esa-oceancolour-cci.org.

393

394 **5** Conclusions

395 The derived observational data product presented here provides a 25-year continuous record of key phytoplankton 396 seasonal cycle metrics (phytoplankton bloom phenology, bloom seasonality and bloom magnitude) on a global-397 scale. It includes three different phenology detection methods that are widely used by the community. We do not 398 advocate for a particular method over another, the strengths and weaknesses of these different approaches have 399 been highlighted in other studies (e.g., Brody et al., 2013), it is up to the user to choose which (if not all) is the 400 most appropriate for their research applications. The data product is also provided at three different horizontal 401 resolutions (4, 9 and 25 km) for regional versus global-scale application. This product is applicable for a broad 402 range of national to international research and industry applications. Its primary strength is that it can be used to 403 assess, monitor, and understand regional to global-scale characteristics in phytoplankton phenology and to detect

- 404 change associated with environmental drivers, which is critical for effective management of marine ecosystems
- 405 and fisheries. This data product will undergo regular updates for future applications and extended time series
- 406 analysis, which typically happens every two years. It will also be updated when data is temporally extended or
- 407 when the OC-CCI releases any version updates beyond v.6.0 that will include backwards corrections for previous
- 408 years, so the entire dataset aligns with the latest version of OC-CCI. This preactive helps to prevent the retention
- 409 of erroneous values within the data set.

410 Appendix A



412

413 Figure A1: Examples of phytoplankton bloom seasonal cycles and comparisons in phenological detection

- 414 methods at key sustained observing stations across the global ocean. For (a) Hawaii Ocean Time-series (HOT,
- 415 21° 20.6'N, 158° 16.4'W), (b) Southern Ocean Time Series Observatory (SOTS, 140°E, 47°S), (c) Bermuda
- 416 Atlantic Time-series Study (BATS, 31° 50' N, 64° 10'W) and (d) Porcupine Abyssal Plain (PAP-SO, 49°N,
- 417 16.5°W) sustained observatory time-series.
- 418



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Figure A2. Comparisons between phenological detection methods. The climatological means [1998 - 2022] for (a-c) bloom initiation, (g-i) bloom termination, and (m-o) bloom duration. The differences between the climatological means for the biomass-based threshold method (TS), the cumulative biomass-based threshold method (CS) and the rate of change method (RC) are provided for bloom initiation (d-f), bloom termination (j-l) and bloom duration (p-r).

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- 427 TRJK, SN, NC. Visualisations: SN, TJRK. Writing original draft: SN. Writing, reviewing, and editing:
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