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Climate-driven reorganisation of global phytoplankton bloom phenology

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Abstract

Marine phytoplankton blooms shape ecosystem health, food security, and climate by underpinning marine food webs and driving ocean carbon uptake. Yet how bloom phenology is changing across ocean biomes, what physical drivers underpin these changes, and whether Earth System models reproduce them remains poorly constrained. Using 27 years of global satellite chlorophyll observations, we identify widespread shifts in phytoplankton bloom timing, duration, magnitude, and seasonality across all major ocean biomes. Across polar regions, blooms are initiating, peaking, and terminating earlier; increasing bloom duration by 0.7-1.3 days year⁻¹. In contrast, most subpolar regions exhibit bloom shortening of 0.5-1.8 days year⁻¹, while subtropical regions show more spatially heterogeneous changes. Across biomes, these changes are most strongly associated with ocean warming, declining sea-ice concentration, and changes in mixed layer dynamics. However, the magnitude, and often the direction, of observed phenological trends differs from Earth system model projections, indicating that the models assessed here do not reproduce important contemporary ecosystem responses to climate change. These findings provide observational evidence that marine phytoplankton seasonality is already undergoing widespread reorganisation and highlight the need to improve model representation of biological responses to a changing ocean.

Main

The seasonal greening of the global ocean by phytoplankton blooms plays a central role in regulating Earth's climate and sustaining marine ecosystems. Through primary production, phytoplankton drive the biological carbon pump, transferring atmospheric CO₂ to the ocean interior and maintaining

atmospheric CO₂ concentrations at approximately half of what they otherwise would be (DeVries, 2022). They also influence planetary radiative forcing through the production of trace gases that affect cloud formation and Earth's albedo (Charlson et al., 1987; McCoy et al., 2015). Beyond their role in climate regulation, phytoplankton support marine food webs (Field et al., 1998) and ultimately global fisheries (Chassot et al., 2010; Stock et al., 2017), which provides approximately 20% of the animal protein consumed by more than 3.3 billion people worldwide (Viana et al., 2023). Given their central role in regulating marine ecosystems, ocean carbon storage and climate feedbacks, understanding how phytoplankton blooms respond to ongoing climate change is essential for predicting future change in the Earth system.

The seasonal cycle of light, surface heating, mixed-layer dynamics, wind, and sea-ice governs much of the environmental variability that regulates phytoplankton growth across the global ocean. Long-term climate change is altering these same physical drivers (Cheng et al., 2020; Sallée et al., 2021; Young & Ribal, 2019), making changes in phytoplankton seasonality a powerful indicator of ecosystem responses to a warming ocean (Thomalla et al., 2011, 2023). Phytoplankton phenology, the timing and characteristics of seasonal blooms, provides a quantitative framework for characterising these responses (Racault et al., 2012; Thomalla et al., 2011), and has emerged as a sensitive indicator of climate-driven ecosystem change (Guest et al., 2026; Henson et al., 2018). Shifts in bloom timing, duration and magnitude can alter seasonal carbon fixation, trophic synchrony and community composition, with important consequences for marine food webs and biogeochemical cycling (Barnes, 2018; Rogers et al., 2019).

Earth System models (ESMs) project substantial shifts in phytoplankton bloom phenology over the twenty-first century (~5 days per decade, Henson et al., 2018; Yamaguchi et al., 2022). Such changes at the base of the marine food web are expected to propagate through ecosystems, potentially leading to future trophic desynchronisation, community reorganisation and altered ocean carbon storage (Ji et al., 2010; Kwiatkowski et al., 2019; Tittensor et al., 2021). Consequently, ESMs have become essential tools for projecting the impacts of climate change and informing adaptation and mitigation policy. Recent work suggests that confidence in future projections of marine primary productivity depends strongly on how well ESMs represent the contemporary seasonal cycle, particularly at high latitudes (Le Grix & Tagliabue, 2026). However, substantial uncertainty remains in how well these models represent seasonal phytoplankton dynamics (Keerthi et al., 2025; Mashifane et al., 2025), while emerging discrepancies with satellite observations (Ryan-Keogh et al., 2025) highlight the need to evaluate whether contemporary changes in phytoplankton phenology are consistent with those models used to project future climate change.

Here, we use 27 years of satellite-derived chlorophyll-a (chl-a) concentrations as a proxy for phytoplankton biomass to quantify changes in phytoplankton bloom phenology across the global ocean (See Methods). Although chl-a reflects photoacclimation and community composition in addition to biomass, it remains the most widely used observational proxy for large-scale phytoplankton dynamics and is well suited to detecting patterns and long-term changes in bloom phenology. Here we identify widespread regional shifts in bloom timing, magnitude and seasonality. In addition, we identify which potential physical drivers most closely align with these trends and compare these observed changes with projections from an ensemble of ESMs. Our results reveal that contemporary phenological change is closely associated with ocean warming, declining sea-ice concentration and mixed layer variability, but the magnitude, and often the direction, of observed trends differs substantially from model projections under continued climate forcing.

Widespread shifts in global phytoplankton phenology

Our analysis of 27 years of satellite observations reveals widespread changes in the timing, magnitude, and seasonality of phytoplankton blooms across the global ocean (Fig. 1). Although the direction and magnitude of these trends vary regionally, coherent spatial patterns emerge that closely follow ocean biome boundaries of Fay & McKinley (2014) and exhibit strong hemispheric symmetry. This basin-scale organisation is indicative of contemporary changes in phytoplankton bloom phenology that are associated with large-scale physical climate forcing. To examine these responses in the context of distinct oceanographic regimes, we describe the observed changes and their most strongly associated physical drivers separately for the polar, subpolar, and subtropical-tropical biomes.

Polar regions: earlier, longer and larger blooms with changing seasonality

Across both polar oceans, significant trends towards earlier bloom initiation averaged 0.8-1.2 days yr⁻¹ across the ice biomes ($p < 0.05$), amounting to a ~22-32-day advance over the 27-year satellite record (Fig. 1a-b, refer to Supplementary Material Table S1). Similar advances were observed in bloom peak timing (Fig. 1g, h), while bloom termination also shifted earlier where significant trends occur (~0.4-0.7 days yr⁻¹, Table S1), although these changes were less spatially widespread than those in initiation (Fig. 1c, d). Consequently, bloom duration increased throughout much of the Arctic and Antarctic, extending the seasonal bloom window by approximately 24-36 days over the observational record (Fig. 1e-f). Bloom seasonality also changed markedly, with seasonal cycle reproducibility (SCR) increasing across much of the Arctic but declining throughout the Antarctic (Fig. 1 i-j), indicating increasingly repeatable seasonal blooms in the north but greater interannual and subseasonal variability in the south. Bloom integrated chl-a increased across both polar regions, most strongly in the Arctic (Fig. 1, 1-6.4 mg m⁻³ d yr⁻¹), consistent with the longer growing season and previous reports of

increasing polar primary productivity (Lewis et al., 2020; Ryan-Keogh et al., 2025; Silsbe et al., 2025). These observations are consistent with earlier regional studies documenting widespread advances in bloom phenology across polar marine ecosystems (Kahru et al., 2011; Thomalla et al., 2023).

These observed phenological changes are consistent with the rapid physical transformation of the polar ocean under climate change (Fig. 2). Sea-ice concentration change emerges as a dominant driver across several of the phenological metrics (Fig. 2a-l). Arctic sea-ice extent has declined by $\sim 4.7\%$ decade⁻¹ (Yadav et al., 2020 and Fig. 2b-n, Supplementary Fig. S1), while recent observations suggest that the Antarctic may be transitioning into a new low-ice regime following unprecedented sea-ice losses since 2016 (Hobbs et al., 2024; Silvano et al., 2025). Reduced sea-ice cover lengthens the ice-free growing season, increasing light availability and extending the seasonal window for phytoplankton growth (Arrigo et al., 2008; Ferreira et al., 2024). Additional processes associated with sea-ice decline, including enhanced frontal activity driven by meltwater input (Giddy et al., 2021) and greater exposure to wind-driven mixing (Timmermans & Marshall, 2020), may further enhance nutrient supply and contribute to the observed increases in bloom duration and magnitude (Fig. 1). The contrasting SCR responses suggest that while Arctic warming is promoting increasingly predictable seasonal blooms, declining seasonality in the Antarctic sea-ice biome is associated with enhanced winter mixing, with annual maximum mixed layer depth (MLD_{max}) emerging as the dominant driver associated with declining SCR (Fig. 2). These changes are indicative of a restructuring of polar marine ecosystems (e.g. Ardyna & Arrigo, 2020; Brandt et al., 2023; Hayward et al., 2025) with the potential to enhance future carbon export from high latitude oceans (Lewis et al., 2020), while altering phytoplankton community composition and trophic interactions in regions that play a disproportionate role in global biogeochemical cycling.

Subpolar biomes: later initiation, earlier termination, shorter blooms of greater magnitude and increased seasonality

In contrast to the polar regions, the northern and southern subpolar biomes exhibited widespread reductions in bloom duration, with significant trends averaging -0.5, -0.05, -1.8 days yr⁻¹ ($p < 0.05$), in the North Pacific, North Atlantic and Southern Ocean subpolar biomes, respectively (Fig. 1e, f and Table S1). These shorter blooms resulted primarily from later bloom initiation and earlier termination (Fig. 1a-f), although the North Pacific was an exception, where bloom termination occurred progressively later (0.3 days yr⁻¹, $p < 0.05$). The strongest and most spatially coherent phenological changes occurred in the Gulf of Alaska, particularly for bloom initiation, and the subpolar Southern Ocean, where bloom duration declined by up to ~ 4 days yr⁻¹ ($p < 0.05$) (Fig. 1f), which amounts to a substantial decline in bloom duration on the order of 100 days over the observed period. Despite these shorter blooms, bloom integrated chl-a increased across much of the northern subpolar biomes (Fig.

1k, l), indicating greater seasonal biomass accumulation within a compressed growing season. Seasonality also generally increased throughout the subpolar oceans (Fig. 1i, j), although regional differences remained evident.

Unlike the polar oceans, the dominant physical contributors varied substantially between subpolar basins, with warming associated with delayed bloom initiation across the North Pacific, MLD_{max} contributing most strongly in parts of the North Atlantic and increasing wind speed dominating the Southern Ocean subpolar biome (Fig. 2). These regional differences nevertheless point to a common influence of upper-ocean mixing on subpolar bloom development. Changes in sea surface temperature, MLD and wind forcing modify the seasonal evolution of stratification, thereby regulating light availability, nutrient resupply and phytoplankton retention, consistent with previous studies identifying mixed-layer dynamics as a primary control on subpolar bloom phenology (Behrenfeld, 2010; Yang et al., 2020). The increase in bloom-integrated chl-a despite shorter bloom durations suggests that enhanced winter nutrient replenishment may partially offset the reduced growing season by supporting greater biomass accumulation during the bloom. Similar behaviour has been reported in the Gulf of Alaska, where regional warming (0.22 ± 0.10 °C decade⁻¹; (Danielson et al., 2022) and increasing marine heatwave occurrence have coincided with rising surface chl-a concentrations and shifts from diatom-dominated communities towards smaller flagellated taxa (Arteaga & Rousseaux, 2023). Such changes have been linked to reduced trophic transfer efficiency, restructuring of higher-trophic levels, and declines in krill abundance and commercially important fisheries (Almeida et al., 2024; Strom, 2023).

Subtropical and tropical biomes: contrasting bloom duration and changing seasonality

Compared with the polar and subpolar regions, changes in phytoplankton bloom phenology across the subtropical and tropical biomes were more spatially heterogeneous (Fig.1). Trends in bloom initiation and termination occurred in both directions (Fig. 1a-d). Bloom duration showed a contrasting hemispheric pattern (Fig. 1e, f), with increasing trends averaging $+0.25$ and $+0.17$ -days yr⁻¹ ($p < 0.05$) in the North Pacific and North Atlantic subtropical biomes, respectively, with stronger decreasing trends in the South Atlantic and Indian Ocean subtropical biomes, by -1.03 - and -0.98 -days yr⁻¹ ($p < 0.05$), respectively (Fig. 1 and Table S1). This contrast was predominantly associated with opposing hemispheric trends in bloom initiation, with a tendency towards earlier initiation in the Northern Hemisphere and later initiation in the Southern Hemisphere (Fig. 1a, b). SCR generally increased throughout the oligotrophic subtropics, indicating increasing consistency in bloom seasonality despite regional variability in the underlying phenological metrics (Fig. 1i, j). Trends in bloom-integrated chl-a were similarly heterogeneous, with widespread declines across the subtropical gyres but localized increases in regions influenced by equatorial upwelling and western boundary current systems (Fig.

1k,l). Together, these results suggest that low latitude phytoplankton phenology is responding less uniformly to climate change than at higher latitudes, reflecting the diverse physical regimes that characterise the tropical and subtropical oceans.

Surface warming emerged as dominant environmental contributor across much of the subtropical gyres. This is consistent with the strong sensitivity of phytoplankton to temperature and nutrient availability in oligotrophic subtropical waters (Fernández-González et al., 2022). Warming can enhance ocean upper-ocean stratification altering mixed-layer dynamics and nutrient supply, and subsequently phytoplankton seasonality (Matsumoto et al., 2021; Racault et al., 2012). In contrast, changes in mixed-layer depth and wind forcing were more important in regions where seasonal mixing or wind-driven upwelling exert stronger controls, including the equatorial Pacific. These regional contrasts highlight the importance of local processes in modulating phenological responses to a warming climate. While the contraction of bloom duration and declining bloom-integrated chl-a in the Southern Hemisphere subtropical biomes may reflect increasing nutrient limitation under enhanced upper-ocean stratification, the tendency towards longer bloom durations in the Northern Hemisphere subtropical gyres suggests that warming does not translate into a uniform phenological response across these nutrient-limited systems. Overall, the broad influence of surface warming, together with substantial regional variability in the importance of other physical drivers, is consistent with Guest et al. (2026), who identified sea surface temperature as the dominant large-scale driver of phytoplankton phenology change.

Together, these global patterns demonstrate that phytoplankton bloom phenology is already undergoing widespread reorganisation in response to contemporary climate change. The close association between observed phenological trends and changes in sea surface temperature, sea-ice concentration, MLD and wind forcing suggests that ongoing physical changes to the upper ocean are reshaping marine ecosystems, with potentially far-reaching consequences for food web structure and ocean carbon cycling (e.g. Almeida et al., 2024; Ardyna & Arrigo, 2020; Brandt et al., 2023). Next, we compare contemporary satellite-observed trends in phytoplankton phenology with projected 21st century trends from ESMs to assess whether the phenological changes emerging in the observational record are consistent with those projected under continued climate forcing.

Disagreements between observed and projected changes of phytoplankton bloom characteristics under 21st century climate forcing

ESMs project substantial future changes in phytoplankton bloom phenology under continued climate forcing, with our CMIP6 ensemble reproducing the broad spatial patterns reported in previous studies (Fig. S2 and S3) (Henson et al., 2018; Payne et al., 2025; Yamaguchi et al., 2022). However,

comparison with contemporary satellite observations reveals widespread disagreement in both the magnitude and, frequently, the direction of projected change (Fig. 3). Across 102 biome-metric comparisons, 65% of the projected trends were consistent with the observed direction of change, while the remaining 35% projected the opposite sign. These discrepancies indicate that, despite broad agreement on the sensitivity of phytoplankton phenology to climate change, substantial uncertainty remains in how ESMs represent the regional expression of these changes.

The strongest model-observation disagreements occurred in the Northern and Southern Hemisphere subpolar biomes, where projected trends in bloom initiation and termination frequently opposed those observed from satellite records (Fig. 3a, b). These regions also exhibited some of the largest and most spatially coherent observed phenological trends (Fig. 1a, b), with mixed-layer variability and wind forcing identified as the dominant physical drivers (Fig. 2). The correspondence between regions of strong observational change, sensitivity to upper-ocean physical forcing, and model disagreement suggests that deficiencies in the representation of upper ocean processes may contribute to these discrepancies. Subpolar bloom development is highly sensitive to mixed-layer evolution and mesoscale variability, processes that remain only partly resolved in coarse-resolution ESMs (Lévy et al., 2018). Consistent with this interpretation, the largest simulated MLD biases occur in the subpolar North Atlantic and Southern Ocean (Treguier et al., 2023), coinciding with the regions of greatest phenological disagreement identified here. Although the present analysis does not isolate the specific mechanisms responsible for these discrepancies, the results identify upper ocean physics as a likely source of model uncertainty.

In contrast, agreement between observations and ESMs was generally stronger across the oligotrophic subtropical gyres, where both indicated relatively modest phenological change, although differences in trend magnitude remained common. These discrepancies may reflect uncertainties in how ESMs represent warming-induced changes in upper-ocean stratification and nutrient supply, which exert primary controls on productivity in oligotrophic regions (Behrenfeld et al., 2006). Among the sea-ice biomes, ESMs generally reproduced the observed direction of phenological change, with both the Arctic and Antarctic exhibiting earlier, longer and more intense blooms in response to declining sea-ice cover (Fig. S3, Payne et al., 2025). However, projected trends in the Antarctic sea-ice biome were consistently weaker than those observed, and the models failed to reproduce the observed decline in seasonality (Fig. 3e). More broadly, changes in seasonality exhibited the weakest agreement of all phenological metrics across the global ocean (Fig. 3e), with opposite-sign trends and large model-observation differences occurring across many biomes. This suggests that current ESMs more successfully reproduce changes in the mean timing of phytoplankton blooms than changes in their characteristics of variability, highlighting persistent deficiencies in representing the physical processes that govern interannual and intraseasonal variability in marine ecosystems.

Our results demonstrate that contemporary climate change is already driving a widespread reorganisation of phytoplankton bloom phenology across the global ocean. Significant changes are evident across all major ocean biomes and are consistently associated with changes in sea surface temperature, wind forcing, mixed-layer dynamics and sea-ice conditions, demonstrating that phytoplankton phenology is already responding to ongoing changes in the physical climate system. Given the central role of seasonal phytoplankton blooms in regulating carbon export, marine food webs and ocean–climate feedbacks, these phenological changes are likely to have important ecological and biogeochemical consequences. Although current-generation ESMs capture some broad patterns of phenological change, they frequently fail to reproduce the magnitude, and often the direction, of contemporary observed trends, particularly in regions where bloom dynamics are strongly coupled to upper ocean physical processes. These findings suggest that key mechanisms governing ecosystem responses to climate change remain incompletely represented in current models. Improving the representation of phytoplankton phenology within ESMs will therefore be essential for increasing confidence in projections of future ocean carbon uptake, marine ecosystem resilience and the effectiveness of climate adaptation and mitigation strategies.

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Author Contributions

All authors conceived the study. SN, TJRK and NC performed the analysis, wrote the code and produced the figures. All authors contributed to the interpretation of the results. SN took the lead in writing the manuscript, with input from TJRK and SJT.

Methods

Remote sensing surface chlorophyll-a data and pre-processing

Satellite-derived chl-a concentrations (mg m^{-3}) were obtained from the European Space Agency Ocean Colour Climate Change Initiative (OC-CCI v6.0; Sathyendranath et al., 2019, 2023) at 4 km spatial and 8-day temporal resolution. The dataset spans the global ocean from 29/08/1997 – 27/12/2024. Chl-a data were regridded to a regular 25 km grid using bilinear interpolation implemented in xESMF (Zhuang et al., 2023). Remaining small data gaps were filled using sequential linear interpolation in longitude, latitude and time (Racault et al., 2014), with interpolation limited to a maximum of two consecutive missing grid cells to avoid filling large regions of persistent missing data while ensuring complete annual time series required for phenology calculations.

CMIP6 Earth System Models

Future changes in global phytoplankton bloom characteristics were investigated using simulations from the CMIP6 under the high emissions climate SSP5-8.5 scenario (2015-2100). Five ESMs providing daily surface chl-a output were selected: CNRM-ESM2-1 (Séférian et al., 2019), MPI-ESM1-2-HR and MPI-ESM1-2-LR (Mauritsen et al., 2019), NorESM2-LM and NorESM2-MM (Seland et al., 2020). These models were selected because daily chl-a output is required for robust estimation of bloom phenology, whereas monthly output has been shown to be insufficient for resolving phenological metrics (Henson et al., 2018). Daily chl-a fields were aggregated to 5-day means to reduce high-frequency variability while preserving bloom timing, and subsequently regridded to a regular $1^\circ \times 1^\circ$ grid using bilinear interpolation implemented in Climate Data Operators (Schulzweida, 2023). The selected models represent multiple biogeochemical models of varying complexity, including PISCES-v2, iHAMOCC and HAMOCC6.

Phytoplankton bloom seasonal metrics calculations

Key phenological characteristics of phytoplankton blooms include the timing of bloom initiation, peak biomass, termination, bloom duration, SCR, and bloom integrated chl-a. These metrics were calculated following the global phenology framework of Nicholson et al. (2025), which extends the Southern Ocean methodology of Thomalla et al. (2023) for application across contrasting oceanographic regimes. The resulting global phenology dataset was used throughout this study.

Nicholson et al. (2025) evaluated three commonly used phytoplankton bloom detection approaches described by Brody et al. (2013), together with the influence of spatial resolution on derived phenology metrics. Based on this assessment, the biomass-threshold method was chosen because differences among detection methods had a minor impact on the resulting phenology metrics and their long-term trends (Figure S4).

A single modification was made to the peak-identification procedure described by Nicholson et al. (2025). Secondary bloom peaks were identified only when they exceeded 75% of the dominant annual peak and were separated by at least three 8-day timesteps. Peak identification proceeded iteratively outward from the dominant peak and terminated when no additional qualifying peaks were detected within 11 consecutive 8-day timesteps. This modification reduced the likelihood of identifying spurious bloom peaks in regions exhibiting extended periods of low chl-a variability.

For the biomass-threshold method, bloom initiation was defined as the first date preceding the bloom maximum, or the first peak in the case of multi-modal blooms, at which chl-a exceeded the minimum concentration plus 5% of the chl-a range, where the range was calculated between the bloom maximum and the minimum concentration preceding the first peak (Henson et al., 2018; Thomalla et al., 2023). Bloom termination was defined as the first date following the bloom maximum at which the chl-a fell below the same threshold. Bloom duration was calculated as the time between initiation and termination, while bloom integrated chl-a was calculated by integrating chl-a over this period.

Seasonal cycle reproducibility (SCR) was calculated as the Pearson correlation between each annual chl-a time series and the climatological seasonal cycle following (Thomalla et al., 2011, 2023). To avoid artificially separating the end of one bloom from the beginning of the next in regions where bloom timing does not align with the calendar year, annual cycles were defined relative to the climatological bloom maximum rather than fixed January-December years. Specifically, annual time series were extracted using a 12-month window centred on the climatological bloom maximum (± 6 months), ensuring that complete bloom cycles were represented consistently across regions with contrasting seasonal regimes.

Trend Analysis

Temporal trends in bloom phenology metrics were quantified for both satellite observations and ESM simulations using a non-parametric trend framework. Grid cells with fewer than 14 years of valid satellite observations were excluded from the analysis. For date-based phenology metrics (bloom initiation, bloom termination and bloom peak date), trends were calculated using relative day of year

anomalies to account for the circular nature of the calendar. Statistical significance was assessed using the Yue-Wang modified Mann-Kendall test (Yue & Wang, 2004), which adjusts the variance of the Mann-Kendall statistic to account for serial autocorrelation. Trend magnitude was quantified using Sen's slope estimator (Sen, 1968),

$$\beta = \text{median} \left\{ \frac{x_j - x_i}{t_j - t_i} : 1 \leq i < j \leq n \right\},$$

where x_i and x_j are the observations at times t_i and t_j , respectively, and n is the number of observations in the time series. Sen's slope provides a robust estimate of monotonic change that is insensitive to outliers and does not require normally distributed residuals. Statistical significance was evaluated at $\alpha = 0.05$.

The same trend analysis was applied consistently to both observational and ESM-derived phenology metrics, allowing the magnitude, direction and spatial organisation of contemporary observed trends (1998–2024) to be compared consistently with projected future trends (2015–2100). Because the observational and model periods represent different stages of anthropogenic climate forcing, direct equivalence in trend magnitude is not expected. Rather than comparing contemporaneous time periods, this framework evaluates whether the trajectory of biological change already emerging in the observational record is consistent with the long-term response projected by Earth System Models under continued climate forcing. Unlike comparisons based on historical and end-of-century climatological means, this approach directly quantifies changes in the seasonal cycle itself, providing an observational benchmark for evaluating projected phenological change.

Driver Analysis

To identify the dominant environmental drivers associated with long-term changes in phytoplankton bloom characteristics, annual biome-mean phenology was related to annual biome-mean environmental conditions using standardized multiple linear regression. Five candidate environmental drivers were considered: annual mean sea surface temperature (SST), annual mean wind speed (Wind), annual maximum mixed-layer depth (MLD_{max}), annual minimum mixed-layer depth (MLD_{min}) and annual mean sea-ice concentration (Ice). Sea-ice concentration was included only for sea-ice biomes.

Annual phenology metrics and environmental drivers were first averaged across all grid cells within each Fay & McKinley (2014) biome to produce biome-mean time series. Timing metrics were converted to relative day of year anomalies as described above. Predictor and response variables were standardized to zero mean and unit variance prior to fitting so that regression coefficients were directly comparable among environmental drivers.

For each biome and phenology metric, standardized multiple linear regressions were fitted according to

$$Y^* = \beta_1 X_{SST}^* + \beta_2 X_{Wind}^* + \beta_3 X_{MLD_{max}}^* + \beta_4 X_{MLD_{min}}^* + \beta_5 X_{Ice}^* + \varepsilon,$$

where Y^* is the standardized phenology metric, X^* are the standardized environmental drivers, and β are standardized regression coefficients. Statistical inference was based on heteroskedasticity- and autocorrelation-consistent (HAC) covariance estimates using the Newey-West correction (Newey & West, 1987).

Standardized regression coefficients quantify the sensitivity of phenology to interannual variability in each environmental driver but do not account for differences in the magnitude of long-term environmental change. To estimate each driver's contribution to the observed phenological trend, standardized regression coefficients were multiplied by the standardized long-term trend of the corresponding environmental driver,

$$C_i = \beta_i T_i,$$

where C_i is the standardized contribution of driver i , β_i is the standardized regression coefficient, and T_i is its standardized long-term trend (standard deviations yr^{-1}). The dominant driver was defined as the predictor with the largest absolute standardized contribution,

$$\text{Dominant driver} = \text{argmax } |C_i|.$$

Because environmental drivers such as SST, wind speed, MLD, and sea-ice can be strongly correlated at biome scales, multicollinearity was assessed using variance inflation factors (VIFs; Table S8). VIFs were <5 for all predictors except SST and sea-ice concentration in the North Pacific and North Atlantic sea-ice biomes, where VIFs ranged from 8.04 to 9.74, indicating greater collinearity between these predictors. Multicollinearity can inflate coefficient uncertainty and reduce the statistical significance of individual predictors. Consequently, the regression analysis is interpreted primarily as identifying the environmental variables most strongly associated with observed phenological variability and long-term change in a multivariate sense, rather than providing a unique causal attribution.

Observation-CMIP6 comparison

To evaluate whether projected changes in phytoplankton bloom characteristics are consistent with recent observations, biome-mean phenology trends derived from satellite observations across all grid cells were compared with those simulated by the five CMIP6 ESMs (Supplementary Fig. S2, S3). Sen's slopes and its associated 95% confidence intervals were calculated separately for the

observations and for each model. For each biome and phenology metric, the CMIP6 ensemble was summarised by the median Sen's slope, while inter-model variability (e.g. Supplementary Fig. S2) was quantified using the ensemble standard deviation.

Uncertainty in the observed trend was estimated from the width of the Sen's slope 95% confidence interval,

$$SE_{obs} = \frac{CI_{upper} - CI_{lower}}{3.92},$$

where 3.92 corresponds to the width of a two-sided 95% confidence interval expressed in standard errors.

Model uncertainty was estimated from the spread of the CMIP6 ensemble,

$$SE_{model} = \frac{\sigma_{model}}{\sqrt{N_{model}}},$$

where σ_{model} is the standard deviation of model trends and N_{model} is the number of models.

The standardized model-observation difference was then calculated as

$$Z = \frac{\beta_{model} - \beta_{obs}}{\sqrt{SE_{obs}^2 + SE_{model}^2}},$$

where β_{obs} and β_{model} are the observed and CMIP6 ensemble-median Sen's slopes, respectively. The denominator combines observation uncertainty and CMIP6 ensemble spread in quadrature.

Agreement between observations and CMIP6 projections was assessed using both the direction and magnitude of change. Biomes were first classified according to whether the ensemble-median and observed trends had the same or opposite sign. The magnitude of model-observation difference was then classified using the absolute standardized difference as small ($|Z| < 1$), moderate ($1 \leq |Z| < 2$), or large ($|Z| \geq 2$). Because Z combines observational uncertainty with inter-model spread, it is interpreted as a standardized measure of model-observation agreement rather than as a formal hypothesis test.

Use of generative AI

OpenAI ChatGPT was used during the development of analysis code to assist with code refinement, debugging and optimisation, and during manuscript preparation to improve the clarity and concision of author-written text. All AI-assisted code was reviewed, tested and validated by the authors, and all

resulting analyses and scientific interpretations were independently evaluated by the authors. The authors take full responsibility for the code, analyses and final manuscript.

Data availability

Ocean colour climate change initiative data were retrieved from: <https://www.oceancolour.org/>. CMIP6 data were obtained from: <https://aims2.llnl.gov/>. Mixed layer depths were retrieved from: <https://doi.org/10.48670/moi-00052>. Sea surface temperature, sea-ice concentration, and 10 m wind speed were retrieved from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis. These data are available from the Copernicus Climate Data Store (CDS): <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels>. The resulting phenology data derived from observations and Earth System Model simulations generated by this study are available via the Zenodo repository <https://zenodo.org/records/21918806>.

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Figures

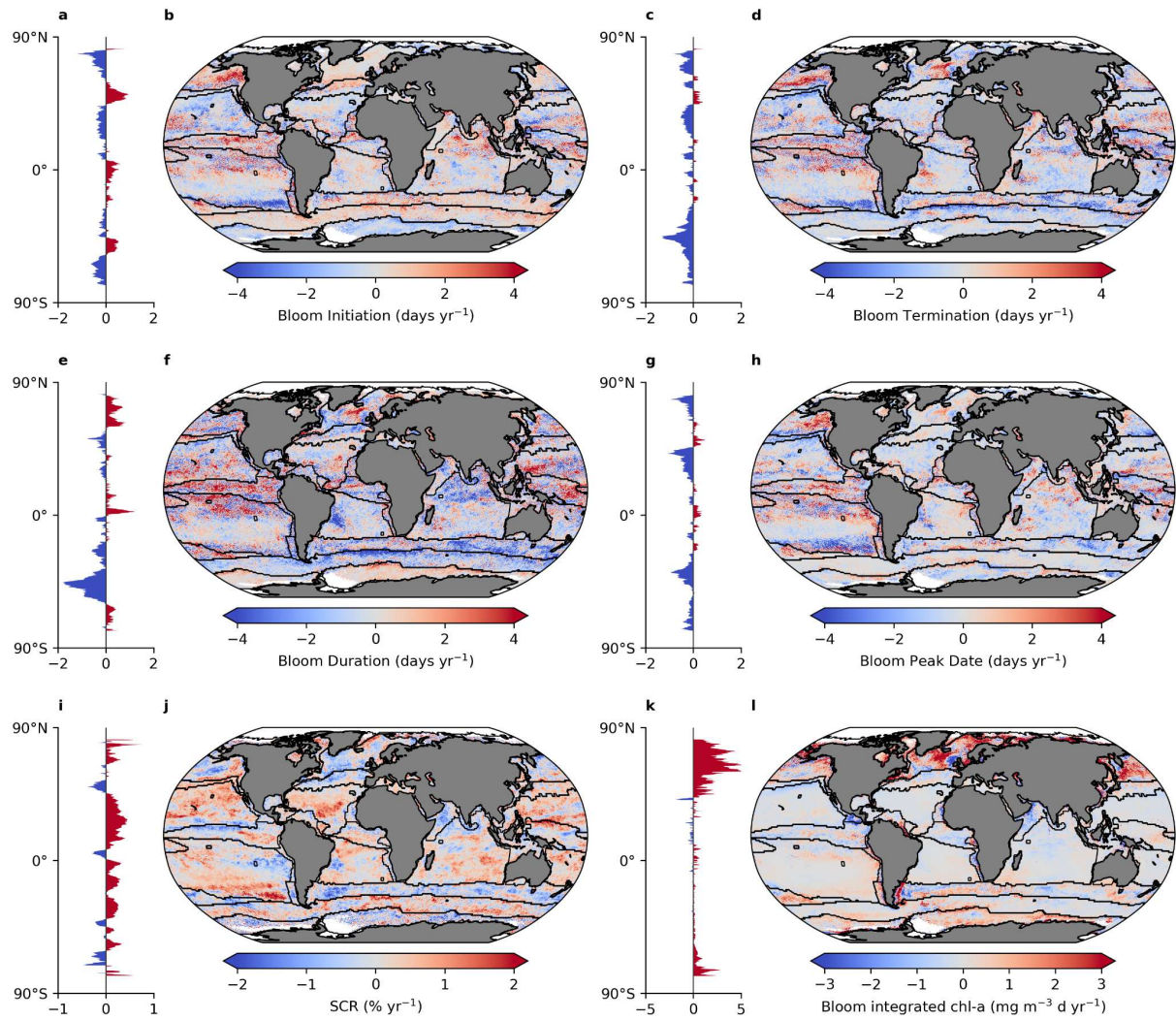


Figure 1: Observed changes in global phytoplankton phenology, magnitude and variability from 1998-2024. Global maps and zonal mean trends in (a, b) bloom initiation (days yr⁻¹), (c, d) bloom termination (days yr⁻¹), (e, f) bloom duration (days yr⁻¹), (g, h) bloom peak date (days yr⁻¹), (i, j) seasonal cycle reproducibility (SCR; % yr⁻¹) and (k, l) bloom integrated chlorophyll-a (mg m⁻³ d yr⁻¹). Solid black lines denote the ocean biome boundaries of Fay & McKinley (2014). Pixels with fewer than 50% temporal data coverage are masked in white.

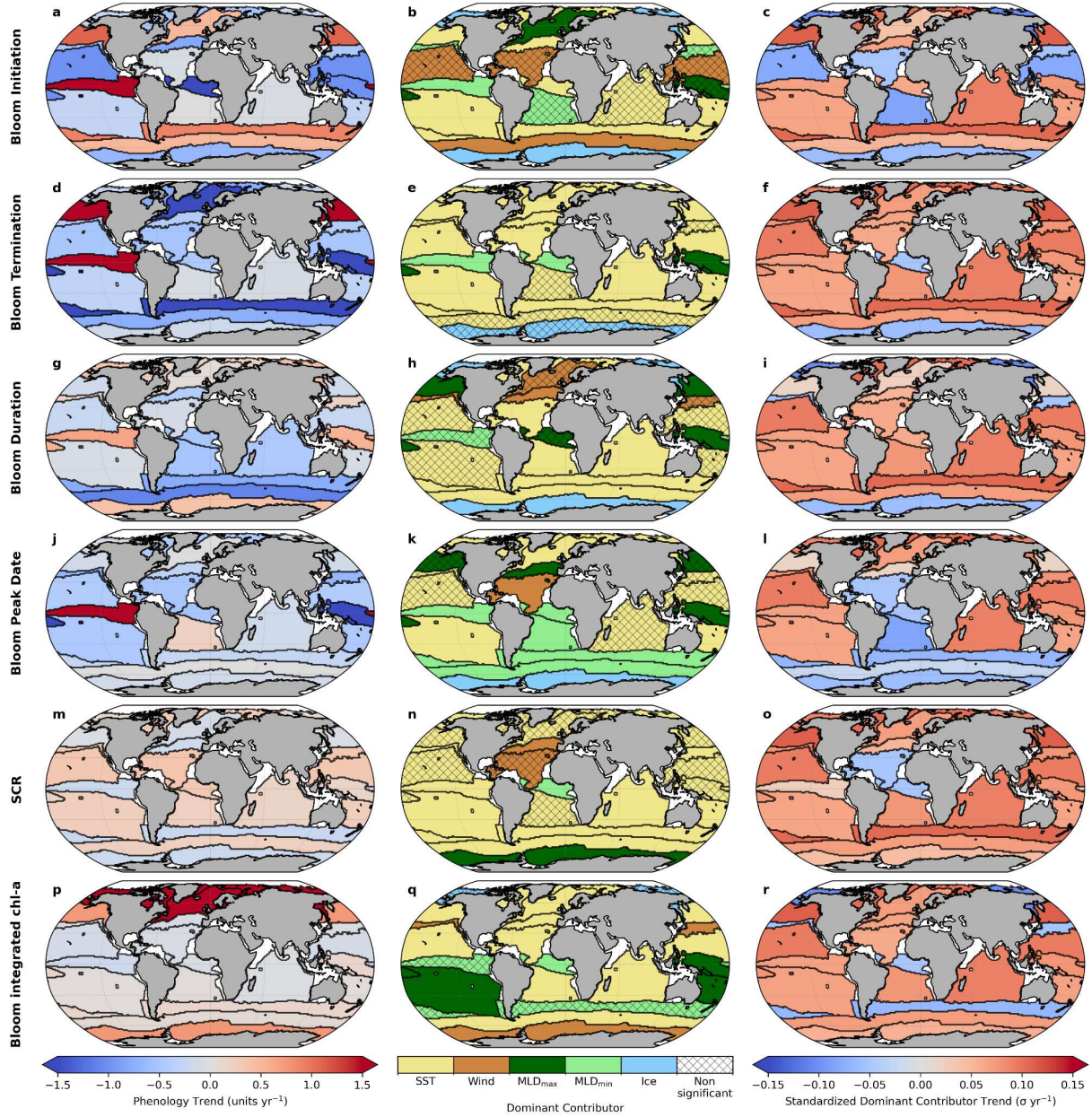


Figure 2: Dominant physical drivers of observed biome-scale changes in phytoplankton bloom characteristics (1998–2024). The left column shows observed biome-mean trend in (a) bloom initiation, (d) bloom termination, (g) bloom duration, (j) bloom peak date, (m) seasonal cycle reproducibility (SCR), and (p) bloom integrated chlorophyll-*a*. The centre column identifies the dominant environmental contributor of each observed trend, determined by multiplying each standardized multiple linear regression coefficient by its standardized long-term trend ($\sigma \text{ yr}^{-1}$). Candidate drivers include annual mean sea surface temperature (SST), annual mean wind speed (Wind), annual maximum mixed-layer depth (MLD_{max}), annual minimum mixed-layer depth (MLD_{min}), and annual mean sea-ice concentration (Ice; sea-ice biomes only). Hatched biomes indicate that no environmental driver was statistically significant (Newey–West corrected, $p > 0.05$). The right column

shows the standardized long-term trend ($\sigma \text{ yr}^{-1}$) of the dominant environmental driver, calculated as the trend of its biome-mean annual time series divided by the standard deviation of that time series. Phenology metrics (left column) and environmental drivers (right column) were spatially averaged within each biome for each year, and trends were calculated from the resulting biome-mean time series; these therefore represent trends in biome-aggregated time series rather than spatial averages of pixel-level trends. Solid black lines denote the ocean biome boundaries of Fay & McKinley (2014).

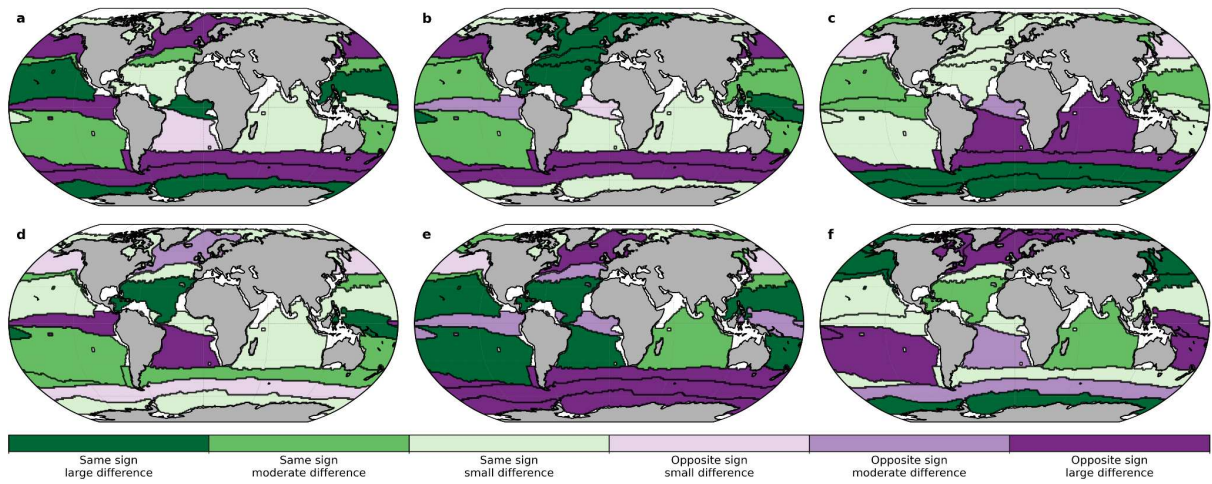


Figure 3: Comparison of biome averaged seasonal bloom trend characteristics between observations and Earth system models. Comparison of observed and CMIP6 ensemble-median trends in (a) bloom initiation, (b) bloom termination, (c) bloom duration, (d) bloom peak date, (e) seasonal cycle reproducibility, and (f) bloom integrated chlorophyll-*a*. Observed trends were calculated for 1998–2024, whereas model trends from CMIP6 SSP5-8.5 simulations over 2015–2100. Agreement is classified according to trend sign and the standardized model–observation difference ($|Z|$), with small ($|Z| < 1$), moderate ($1 < |Z| < 2$), and large ($|Z| \geq 2$) differences. Z combines uncertainty in the observed Sen’s slope estimate with the spread across the CMIP6 ensemble and is interpreted as a standardized measure of model–observation agreement rather than a formal hypothesis test. Solid black lines denote the ocean biome boundaries of Fay & McKinley (2014).

Supplementary Information

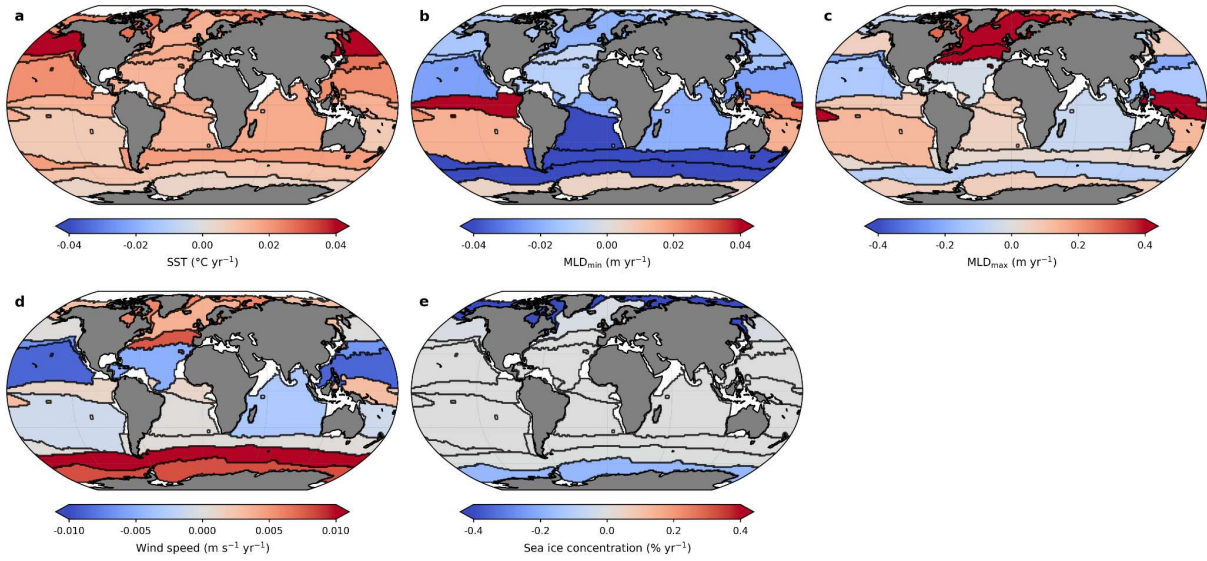


Figure S1: Biome mean trends in the environmental drivers over the satellite observation period (1998–2024). (a) Sea surface temperature (SST), (b) annual minimum mixed-layer depth (MLD_{min}), (c) annual maximum mixed-layer depth (MLD_{max}), (d) wind speed, and (e) sea-ice concentration. Trends are shown as biome means following Fay & McKinley (2014) and provide the explanatory variables used to identify the dominant drivers of phytoplankton phenology trends in Fig. 2. Environmental drivers were spatially averaged within each biome for each year, and trends were calculated from the resulting biome-mean time series; these therefore represent trends in biome-aggregated time series rather than spatial averages of pixel-level trends.

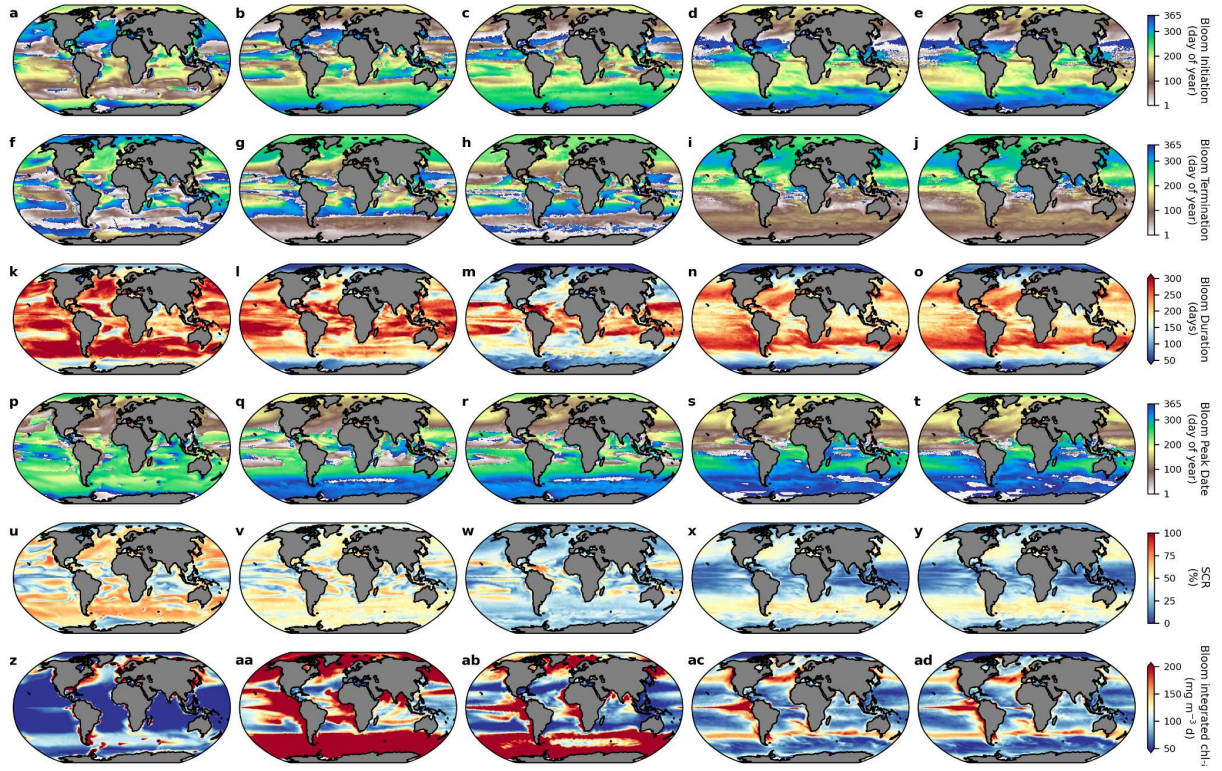


Figure S2: Global climatologies of seasonal bloom characteristics simulated by the five CMIP6 Earth system models used in this study. Mean climatologies of bloom initiation (a-e), bloom termination (f-j), bloom duration (k-o), bloom peak date (p-t), seasonal cycle reproducibility (SCR; u-y), and bloom integrated chlorophyll-a (z-ad) derived from (left to right) CNRM-ESM2-1, MPI-ESM1-2-HR, MPI-ESM1-2-LR, NorESM2-LM, and NorESM2-MM under the SSP5-8.5 scenario (2015-2100). Bloom initiation, termination, and peak date are expressed as day of year, bloom duration as days, SCR as a percentage, and bloom integrated chlorophyll-a as $\text{mg m}^{-3} \text{ d}$.

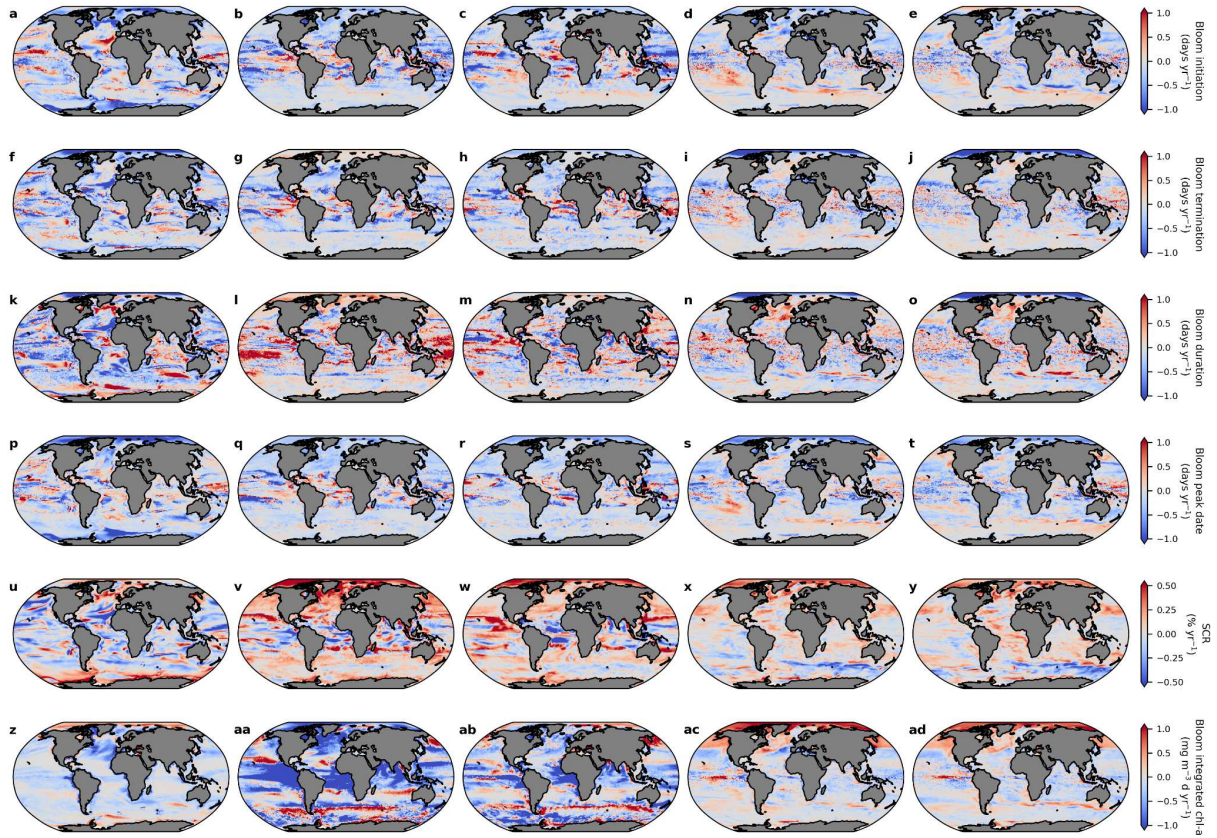


Figure S3: Global trends in seasonal bloom characteristics simulated by the five CMIP6 Earth system models used in this study. Trends in bloom initiation (a-e), bloom termination (f-j), bloom duration (k-o), bloom peak date (p-t), seasonal cycle reproducibility (SCR; u-y), and bloom integrated chlorophyll-a (z-ad) derived from (left to right) CNRM-ESM2-1, MPI-ESM1-2-HR, MPI-ESM1-2-LR, NorESM2-LM, and NorESM2-MM under the SSP5-8.5 scenario (2015-2100). Trends are estimated using the Theil-Sen slope estimator. Units are days yr⁻¹ for bloom initiation, termination, duration, and peak date; % yr⁻¹ for SCR; and mg m⁻³ d yr⁻¹ for bloom integrated chlorophyll-a.

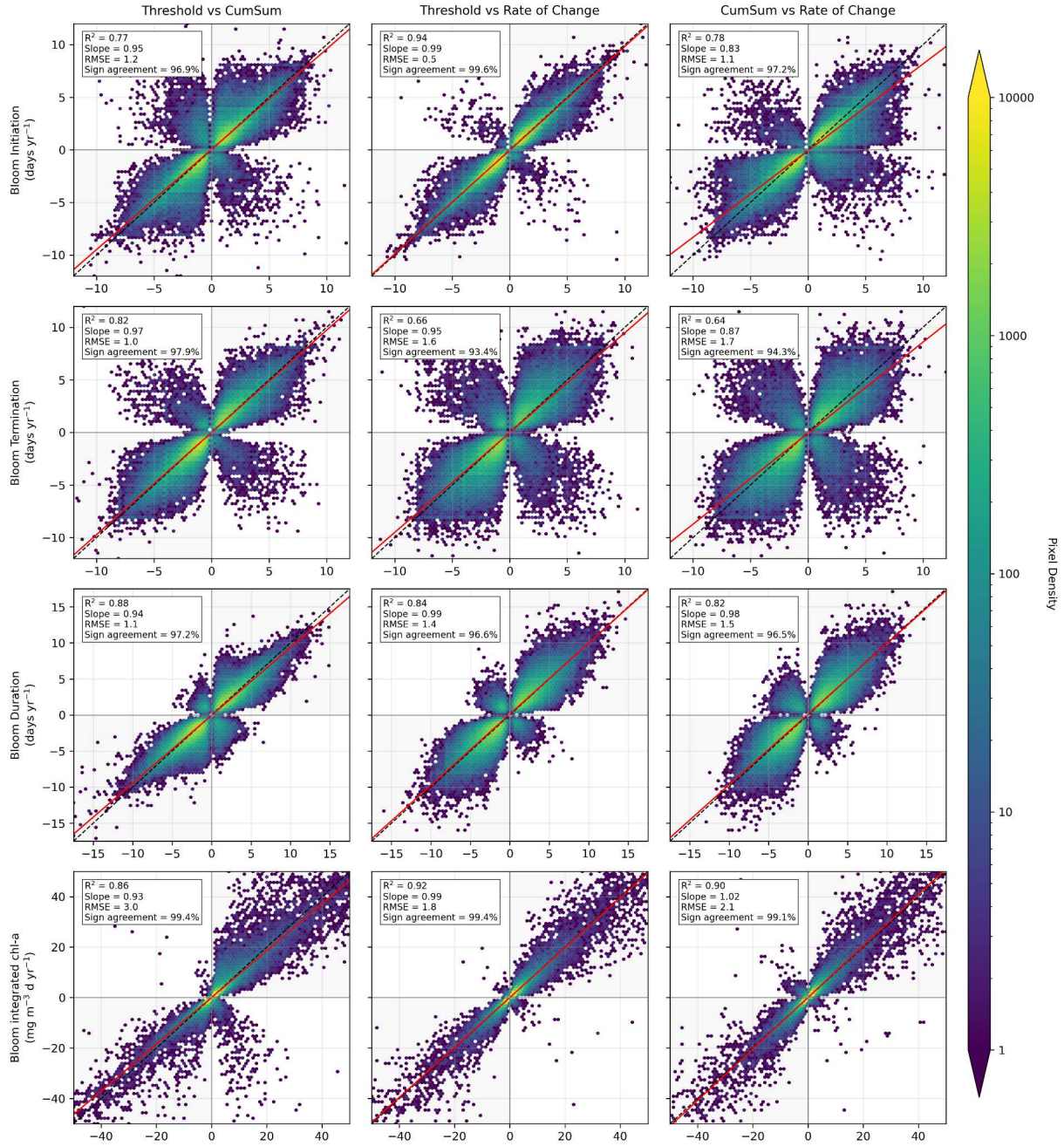


Figure S4: Comparison of phenological trends derived using three bloom detection methods.

Pairwise comparisons of pixel-wise trends derived using the threshold, cumulative sum (CumSum), and rate-of-change methods for bloom initiation, bloom termination, bloom duration, and bloom integrated chlorophyll-a. Each point represents the trend at a single 25 km ocean pixel. Colours indicate pixel density on a logarithmic scale. The dashed black line denotes the 1:1 relationship and the solid red line shows the least-square regression. Insets report the coefficient of determination (R^2), regression slope, root mean square error (RMSE), and the percentage of pixels for which both methods produce trends with the same sign.

Table S1. Area-weighted biome-scale trends in phytoplankton bloom characteristics (1998–2024). Trends are reported for bloom initiation, termination, duration, peak date, seasonal cycle reproducibility (SCR), and bloom integrated chlorophyll-*a* for each Fay and McKinley (2014) ocean biome. For each metric, Mean represents the area-weighted mean trend across all pixels within the biome, while Sig. mean represents the area-weighted mean calculated using only pixels with statistically significant trends ($p < 0.05$). Biome numbers and labels correspond to the Fay and McKinley (2014) biome classification.

Biome		Bloom Initiation (days yr ⁻¹)		Bloom Termination (days yr ⁻¹)		Bloom Duration (days yr ⁻¹)		Bloom Peak date (days yr ⁻¹)		SCR (% yr ⁻¹)		Bloom Integrated Chl-a (mg m ⁻³ d yr ⁻¹)	
		Mean	Sig. mean	Mean	Sig. mean	Mean	Sig. mean	Mean	Sig. mean	Mean	Sig. mean	Mean	Sig. mean
1	NP ICE	-0.74	-1.20	-0.32	-0.58	0.73	1.33	-0.46	-0.85	-0.01	-0.02	4.16	6.44
2	NP SPS S	0.42	0.77	0.18	0.33	-0.24	-0.46	-0.10	-0.17	-0.01	-0.01	0.65	1.06
3	NP STS S	-0.22	-0.47	-0.40	-0.75	0.08	0.14	-0.65	-1.21	0.34	0.52	-0.05	-0.07
4	NP STP	-	-	-	-	0.12	0.2	-0.19	-	0.34	0.53	-	-

	S	0.28	0.51	0.21	0.42		5		0.39			0.11	0.20
5	PEQ U-W	3.14 $\times 10^{-3}$	- 0.02	- 0.30	- 0.58	0.46	0.8 7	-0.12	- 0.23	0.20	0.36	0.07	0.13
6	PEQ U-E	0.58	1.12	0.07	0.10	0.58	1.0 8	0.35	0.68	-0.07	-0.11	- 0.19	- 0.37
7	SP STP S	- 0.13	- 0.26	- 0.20	- 0.38	- 2.27 $\times 10^{-3}$	- 0.0 1	-0.17	- 0.32	0.22	0.35	0.07	0.13
8	NA ICE	- 0.47	- 0.84	- 0.38	- 0.65	0.37	0.6 9	-0.31	- 0.53	0.24	0.41	3.83	5.43
9	NA SPS S	0.26	0.52	- 0.15	- 0.22	- 0.03	- 0.0 5	-0.08	- 0.17	-0.11	-0.19	1.17	1.78
1 0	NA STS S	0.10	0.26	- 0.29	- 0.61	- 0.40	- 0.8 2	-0.08	- 0.14	-0.21	-0.41	- 0.05	- 0.05
1 1	NA STP S	- 0.22	- 0.43	- 0.34	- 0.64	0.09	0.1 7	-0.20	- 0.43	0.33	0.52	- 0.05	- 0.08

1 2	AEQ U	- 0.08	- 0.13	- 0.26	- 0.47	- 0.48	- 0.86	-0.06	- 0.09	0.18	0.31	- 0.14	- 0.25
1 3	SA STP S	- 2.11 $\times 10^{-3}$	- 0.01	- 0.14	- 0.26	- 0.53	- 1.03	-0.03	- 0.06	0.19	0.31	0.03	0.05
1 4	IND STP S	0.13	0.26	- 0.23	- 0.44	- 0.51	- 0.98	-0.10	- 0.21	0.17	0.29	- 0.05	- 0.08
1 5	SO STS S	0.26	0.49	- 0.41	- 0.74	- 0.88	- 1.56	-0.29	- 0.55	-0.26	-0.44	0.15	0.26
1 6	SO SPS S	0.37	0.71	- 0.62	- 1.09	- 1.08	- 1.80	-0.10	- 0.22	0.21	0.37	0.08	0.16
1 7	SO ICE	- 0.66	- 1.06	- 0.17	- 0.36	0.49	0.86	-0.20	- 0.39	-0.21	-0.38	0.60	0.96

Biome-scale multiple linear regression results

Supplementary Tables 2–7 present the full outputs of the biome-scale multiple linear regression analyses used to assess the physical drivers of changes to phytoplankton bloom characteristics over 1998–2024. Results are shown separately for bloom initiation, bloom termination, bloom duration, bloom peak date, seasonal cycle reproducibility (SCR), and bloom integrated chlorophyll-*a*. For each biome, the tables report the adjusted R^2 of the regression model and standardized regression coefficients (β) for each environmental predictor, with Newey–West corrected P values shown in parentheses. Predictors include sea surface temperature (SST), maximum and minimum mixed-layer depth (MLDmax and MLDmin), and wind speed, with sea-ice concentration additionally included in the three sea-ice biomes. Variance inflation factors (VIFs) used to assess multicollinearity among predictors are provided separately in Supplementary Table 8.

Table S2. Multiple linear regression results for interannual variability in bloom initiation across ocean biomes (1998–2024). Adjusted R^2 indicates model explanatory power. Predictor columns report standardized regression coefficients (β), with Newey–West corrected p -values in parentheses. Predictors are annual mean sea surface temperature (SST), annual maximum mixed-layer depth (MLDmax), annual minimum mixed-layer depth (MLDmin), annual mean wind speed (Wind), and annual mean sea-ice concentration (Ice; sea-ice biomes only). Bold values indicate statistically significant predictors ($p < 0.05$). A p -value displayed as <0.01 indicates values rounded to 0.00 in the source table. Biomes follow Fay and McKinley (2014).

Biome	Adj. R^2	SST β (p)	MLDmax β (p)	MLDmin β (p)	Wind β (p)	Ice β (p)
NP ICE	0.18	-1.19 (0.01)	0.20 (0.20)	-0.23 (0.29)	-0.05 (0.72)	-1.07 (0.05)
NP SPSS	0.20	0.50 (0.02)	0.21 (0.37)	-0.17 (0.28)	0.07 (0.67)	—
NP STSS	0.07	0.12 (0.55)	0.48 (0.06)	0.37 (0.09)	-0.11 (0.55)	—

NP STPS	0.36	-0.07 (0.74)	0.05 (0.81)	0.44 (<0.01)	0.25 (0.19)	—
PEQU-W	0.08	-0.12 (0.65)	0.32 (0.43)	-0.71 (0.06)	0.00 (0.99)	—
PEQU-E	0.47	-0.17 (0.38)	-0.50 (<0.01)	1.03 (<0.01)	-0.41 (0.05)	—
SP STPS	0.17	-0.59 (<0.01)	0.19 (0.13)	-0.22 (0.33)	-0.32 (0.09)	—
NA ICE	0.48	-1.51 (<0.01)	-0.18 (0.40)	-0.99 (<0.01)	0.04 (0.78)	-0.28 (0.53)
NA SPSS	0.30	0.12 (0.52)	0.44 (<0.01)	-0.20 (0.21)	0.32 (0.02)	—
NA STSS	0.41	-0.34 (0.01)	0.65 (<0.01)	-0.10 (0.50)	-0.30 (0.04)	—
NA STPS	0.06	0.40 (0.16)	-0.29 (0.32)	-0.09 (0.56)	0.55 (0.16)	—
AEQU	0.33	-0.79 (<0.01)	0.43 (0.04)	0.11 (0.43)	-0.60 (0.01)	—
SA STPS	0.34	0.03 (0.82)	0.63 (<0.01)	-0.16 (0.11)	0.17 (0.25)	—
IND STPS	-0.05	-0.36 (0.05)	0.11 (0.61)	-0.14 (0.45)	-0.22 (0.19)	—
SO STSS	0.43	0.67 (<0.01)	-0.19 (0.33)	-0.13 (0.49)	0.36 (<0.01)	—
SO SPSS	0.26	0.24 (0.04)	-0.02 (0.91)	-0.51 (<0.01)	0.40 (0.02)	—

SO ICE	0.56	-0.32 (0.18)	0.01 (0.96)	0.10 (0.30)	-0.22 (0.04)	0.50 (0.02)
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Table S3. Multiple linear regression results for interannual variability in bloom termination across ocean biomes (1998–2024). Adjusted R^2 indicates model explanatory power. Predictor columns report standardized regression coefficients (β), with Newey–West corrected p-values in parentheses. Predictors are annual mean sea surface temperature (SST), annual maximum mixed-layer depth (MLDmax), annual minimum mixed-layer depth (MLDmin), annual mean wind speed (Wind), and annual mean sea-ice concentration (Ice; sea-ice biomes only). Bold values indicate statistically significant predictors ($p < 0.05$). Biomes follow Fay and McKinley (2014).

Biome	Adj. R^2	SST β (p)	MLDmax β (p)	MLDmin β (p)	Wind β (p)	Ice β (p)
NP ICE	0.23	-1.38 (<0.01)	0.05 (0.80)	-0.35 (0.04)	-0.02 (0.91)	-1.03 (0.02)
NP SPSS	0.15	0.49 (<0.01)	0.31 (0.06)	-0.02 (0.90)	0.10 (0.47)	—
NP STSS	0.18	-0.36 (0.11)	0.04 (0.88)	0.15 (0.28)	0.17 (0.31)	—
NP STPS	-0.03	-0.50 (0.03)	0.05 (0.83)	-0.10 (0.61)	-0.20 (0.27)	—
PEQU-W	0.13	-0.20 (0.05)	-0.64 (<0.01)	0.34 (0.26)	-0.13 (0.41)	—
PEQU-E	0.40	-0.92 (<0.01)	-0.49 (<0.01)	0.76 (<0.01)	-0.79 (<0.01)	—
SP STPS	-0.01	-0.36 (0.02)	-0.00 (0.98)	-0.12 (0.57)	0.11 (0.50)	—
NA ICE	0.55	-1.94 (<0.01)	-0.34 (0.09)	-0.80 (0.01)	0.27 (0.06)	-0.82 (0.05)
NA SPSS	0.28	-0.46 (0.05)	-0.45 (0.03)	0.03 (0.85)	-0.29 (0.03)	—

NA STSS	0.17	-0.51 (<0.01)	-0.01 (0.96)	0.11 (0.62)	-0.09 (0.51)	—
NA STPS	0.18	-0.60 (<0.01)	0.06 (0.66)	0.08 (0.64)	-0.15 (0.25)	—
AEQU	0.21	-0.27 (0.10)	0.08 (0.75)	0.50 (0.03)	-0.03 (0.91)	—
SA STPS	0.26	-0.08 (0.44)	-0.10 (0.63)	0.05 (0.78)	0.59 (<0.01)	—
IND STPS	0.22	-0.61 (0.02)	0.12 (0.54)	-0.29 (0.03)	-0.13 (0.57)	—
SO STSS	0.51	-0.55 (<0.01)	0.10 (0.48)	0.35 (0.01)	-0.10 (0.36)	—
SO SPSS	0.33	-0.20 (0.28)	0.28 (0.18)	0.57 (<0.01)	-0.24 (0.21)	—
SO ICE	0.27	-0.15 (0.54)	0.28 (0.24)	-0.11 (0.42)	-0.21 (0.34)	0.39 (0.18)

Table S4. Multiple linear regression results for interannual variability in bloom duration across ocean biomes (1998–2024). Adjusted R^2 indicates model explanatory power. Predictor columns report standardized regression coefficients (β), with Newey–West corrected p-values in parentheses. Predictors are annual mean sea surface temperature (SST), annual maximum mixed-layer depth (MLDmax), annual minimum mixed-layer depth (MLDmin), annual mean wind speed (Wind), and annual mean sea-ice concentration (Ice; sea-ice biomes only). Bold values indicate statistically significant predictors ($p < 0.05$). Biomes follow Fay and McKinley (2014).

Biome	Adj. R^2	SST β (p)	MLDmax β (p)	MLDmin β (p)	Wind β (p)	Ice β (p)
NP ICE	0.27	-0.05 (0.89)	0.11 (0.34)	0.50 (<0.01)	0.28 (0.23)	-0.84 (0.03)
NP SPSS	0.19	-0.03 (0.82)	-0.59 (<0.01)	0.01 (0.95)	0.31 (<0.01)	—
NP STSS	0.01	-0.04 (0.86)	-0.25 (0.37)	-0.07 (0.74)	-0.21 (0.30)	—
NP STPS	0.06	-0.26 (0.36)	-0.25 (0.39)	-0.39 (0.02)	-0.05 (0.86)	—
PEQU-W	0.52	-0.20 (0.13)	0.76 (<0.01)	0.03 (0.90)	-0.12 (0.35)	—
PEQU-E	0.02	-0.64 (0.03)	-0.12 (0.54)	0.33 (0.19)	-0.40 (0.12)	—
SP STPS	-0.03	-0.29 (0.09)	0.14 (0.56)	-0.02 (0.91)	-0.37 (0.21)	—
NA ICE	0.18	0.93 (<0.01)	0.22 (0.22)	0.52 (0.04)	0.33 (0.12)	0.46 (0.33)
NA SPSS	-0.11	0.05 (0.85)	0.15 (0.60)	-0.00 (0.99)	-0.29 (0.11)	—
NA STSS	0.56	-0.28 (0.02)	-1.09 (<0.01)	0.23 (0.08)	0.42 (<0.01)	—

NA STPS	0.12	-0.65 (0.01)	0.17 (0.57)	-0.01 (0.97)	-0.66 (0.06)	—
AEQU	0.31	0.07 (0.70)	-0.33 (0.10)	-0.31 (0.08)	0.90 (<0.01)	—
SA STPS	0.51	-0.60 (<0.01)	-0.50 (<0.01)	0.16 (0.28)	0.18 (0.16)	—
IND STPS	0.11	-0.50 (<0.01)	-0.20 (0.17)	0.16 (0.12)	-0.04 (0.86)	—
SO STSS	0.43	-0.36 (<0.01)	0.19 (0.20)	0.42 (0.01)	-0.36 (<0.01)	—
SO SPSS	0.45	-0.49 (<0.01)	0.06 (0.67)	0.43 (<0.01)	-0.44 (<0.01)	—
SO ICE	0.42	0.12 (0.37)	0.24 (0.07)	-0.32 (0.01)	0.04 (0.82)	-0.65 (<0.01)

Table S5. Multiple linear regression results for interannual variability in bloom peak date across ocean biomes (1998–2024). Adjusted R^2 indicates model explanatory power. Predictor columns report standardized regression coefficients (β), with Newey–West corrected p-values in parentheses. Predictors are annual mean sea surface temperature (SST), annual maximum mixed-layer depth (MLDmax), annual minimum mixed-layer depth (MLDmin), annual mean wind speed (Wind), and annual mean sea-ice concentration (Ice; sea-ice biomes only). Bold values indicate statistically significant predictors ($p < 0.05$). Biomes follow Fay and McKinley (2014).

Biome	Adj. R^2	SST β (p)	MLDmax β (p)	MLDmin β (p)	Wind β (p)	Ice β (p)
NP ICE	0.26	-1.30 (<0.01)	0.14 (0.45)	-0.30 (0.14)	0.07 (0.66)	-1.08 (0.03)
NP SPSS	-0.08	-0.04 (0.82)	-0.29 (0.05)	-0.05 (0.79)	0.21 (0.40)	—
NP STSS	0.29	-0.26 (0.06)	0.38 (0.13)	0.36 (<0.01)	-0.10 (0.71)	—
NP STPS	0.24	-0.31 (0.21)	0.28 (0.18)	0.24 (0.18)	-0.14 (0.47)	—
PEQU-W	0.39	0.21 (0.21)	-0.83 (<0.01)	0.16 (0.44)	0.14 (0.52)	—
PEQU-E	0.34	0.56 (0.03)	-0.42 (<0.01)	0.54 (<0.01)	0.31 (0.21)	—
SP STPS	0.41	-0.68 (<0.01)	0.13 (0.42)	-0.21 (0.25)	0.13 (0.21)	—
NA ICE	0.45	-1.96 (<0.01)	-0.12 (0.64)	-1.09 (<0.01)	0.21 (0.18)	-0.71 (0.10)
NA SPSS	0.06	-0.35 (0.02)	0.37 (0.07)	-0.21 (0.08)	-0.36 (0.06)	—

NA STSS	0.44	-0.11 (0.40)	0.78 (<0.01)	-0.17 (0.27)	-0.13 (0.40)	—
NA STPS	0.42	-0.00 (1.00)	0.50 (<0.01)	-0.23 (0.19)	0.44 (<0.01)	—
AEQU	0.22	0.06 (0.78)	-0.06 (0.83)	0.58 (0.02)	-0.02 (0.95)	—
SA STPS	0.58	0.28 (<0.01)	0.63 (<0.01)	-0.26 (0.05)	0.45 (<0.01)	—
IND STPS	0.22	-0.31 (0.09)	0.48 (<0.01)	-0.01 (0.96)	-0.17 (0.28)	—
SO STSS	0.41	-0.21 (0.21)	0.17 (0.16)	0.52 (<0.01)	0.07 (0.54)	—
SO SPSS	0.23	-0.12 (0.45)	0.17 (0.28)	0.53 (<0.01)	0.01 (0.94)	—
SO ICE	0.42	-0.04 (0.83)	0.32 (0.11)	0.26 (0.06)	-0.31 (0.09)	0.74 (0.01)

Table S6. Multiple linear regression results for interannual variability in seasonal cycle reproducibility (SCR) across ocean biomes (1998–2024). Adjusted R^2 indicates model explanatory power. Predictor columns report standardized regression coefficients (β), with Newey–West corrected p-values in parentheses. Predictors are annual mean sea surface temperature (SST), annual maximum mixed-layer depth (MLDmax), annual minimum mixed-layer depth (MLDmin), annual mean wind speed (Wind), and annual mean sea-ice concentration (Ice; sea-ice biomes only). Bold values indicate statistically significant predictors ($p < 0.05$). Biomes follow Fay and McKinley (2014).

Biome	Adj. R^2	SST β (p)	MLDmax β (p)	MLDmin β (p)	Wind β (p)	Ice β (p)
NP ICE	0.40	0.65 (0.02)	0.22 (0.11)	-0.02 (0.93)	0.17 (0.26)	-0.08 (0.81)
NP SPSS	-0.13	-0.15 (0.41)	0.01 (0.96)	-0.22 (0.42)	0.06 (0.79)	—
NP STSS	0.26	0.42 (<0.01)	-0.20 (0.30)	-0.03 (0.86)	-0.10 (0.49)	—
NP STPS	0.44	0.36 (0.05)	-0.24 (0.18)	0.01 (0.92)	-0.26 (0.03)	—
PEQU-W	0.04	0.37 (0.12)	0.08 (0.77)	0.10 (0.70)	-0.12 (0.33)	—
PEQU-E	0.22	1.04 (<0.01)	-0.09 (0.45)	-0.29 (0.06)	0.72 (<0.01)	—
SP STPS	0.32	0.70 (<0.01)	-0.08 (0.44)	0.34 (0.07)	-0.01 (0.95)	—
NA ICE	0.62	0.37 (0.37)	0.20 (0.21)	-0.30 (0.14)	-0.16 (0.15)	-0.15 (0.52)
NA SPSS	0.00	0.18 (0.49)	-0.01 (0.97)	0.24 (0.26)	-0.30 (0.21)	—

NA STSS	0.42	-0.06 (0.65)	-0.46 (<0.01)	0.03 (0.85)	-0.35 (0.03)	—
NA STPS	-0.02	0.03 (0.87)	-0.01 (0.94)	-0.25 (0.18)	-0.14 (0.56)	—
AEQU	0.27	0.09 (0.60)	0.20 (0.28)	-0.33 (0.03)	0.51 (0.05)	—
SA STPS	0.09	0.11 (0.54)	-0.20 (0.23)	-0.09 (0.67)	-0.25 (0.18)	—
IND STPS	0.11	0.36 (0.04)	-0.18 (0.29)	-0.05 (0.79)	-0.02 (0.92)	—
SO STSS	0.52	-0.62 (<0.01)	0.19 (0.07)	0.10 (0.39)	-0.60 (<0.01)	—
SO SPSS	0.27	0.43 (<0.01)	-0.31 (0.06)	-0.20 (0.05)	0.20 (0.24)	—
SO ICE	0.15	-0.38 (0.09)	-0.47 (<0.01)	-0.00 (0.99)	0.02 (0.93)	-0.15 (0.55)

Table S7. Multiple linear regression results for interannual variability in bloom integrated chlorophyll-a across ocean biomes (1998–2024). Adjusted R^2 indicates model explanatory power. Predictor columns report standardized regression coefficients (β), with Newey–West corrected p-values in parentheses. Predictors are annual mean sea surface temperature (SST), annual maximum mixed-layer depth (MLDmax), annual minimum mixed-layer depth (MLDmin), annual mean wind speed (Wind), and annual mean sea-ice concentration (Ice; sea-ice biomes only). Bold values indicate statistically significant predictors ($p < 0.05$). Biomes follow Fay and McKinley (2014).

Biome	Adj. R^2	SST β (p)	MLDmax β (p)	MLDmin β (p)	Wind β (p)	Ice β (p)
NP ICE	0.23	0.28 (0.47)	0.05 (0.77)	0.64 (<0.01)	0.10 (0.51)	-0.68 (0.16)
NP SPSS	0.44	0.68 (<0.01)	0.03 (0.82)	0.03 (0.85)	-0.20 (0.26)	—
NP STSS	0.26	-0.36 (0.18)	0.01 (0.96)	0.26 (0.11)	-0.64 (<0.01)	—
NP STPS	0.52	-0.82 (<0.01)	-0.12 (0.52)	0.14 (0.27)	-0.16 (0.26)	—
PEQU-W	0.51	-0.19 (0.27)	0.77 (<0.01)	-0.19 (0.38)	0.28 (0.02)	—
PEQU-E	0.63	-0.50 (0.02)	-0.04 (0.73)	-0.34 (0.09)	0.32 (0.08)	—
SP STPS	0.12	-0.02 (0.87)	0.48 (<0.01)	0.11 (0.48)	-0.22 (0.27)	—
NA ICE	0.79	1.32 (<0.01)	0.40 (<0.01)	0.29 (0.02)	0.35 (<0.01)	0.79 (<0.01)
NA SPSS	0.31	0.53 (0.01)	0.55 (0.01)	-0.19 (0.14)	0.00 (1.00)	—

NA STSS	0.23	-0.43 (0.01)	-0.66 (0.01)	0.27 (0.05)	0.36 (0.11)	—
NA STPS	0.21	-0.48 (0.01)	0.28 (0.06)	0.31 (0.07)	-0.43 (0.03)	—
AEQU	0.38	-0.08 (0.56)	-0.33 (0.06)	-0.61 (<0.01)	0.78 (<0.01)	—
SA STPS	0.24	0.56 (<0.01)	-0.02 (0.89)	0.17 (0.37)	0.57 (<0.01)	—
IND STPS	0.13	-0.39 (0.01)	0.15 (0.30)	-0.15 (0.17)	0.10 (0.68)	—
SO STSS	-0.10	-0.05 (0.79)	-0.05 (0.81)	-0.23 (0.38)	0.15 (0.52)	—
SO SPSS	0.33	0.64 (<0.01)	0.49 (<0.01)	-0.07 (0.60)	-0.17 (0.09)	—
SO ICE	0.06	0.38 (0.29)	0.01 (0.95)	-0.24 (0.21)	0.46 (0.01)	0.07 (0.78)

Table S8. Variance inflation factors (VIFs) for environmental predictors used in the biome-scale multiple linear regression analyses. VIFs are reported for annual mean sea surface temperature (SST), annual maximum mixed-layer depth (MLDmax), annual minimum mixed-layer depth (MLDmin), annual mean wind speed (Wind), and annual mean sea-ice concentration (Ice; sea-ice biomes only). Because the same predictor time series were used for all phytoplankton bloom characteristics within each biome, VIFs are common across the corresponding regression models and are reported only once.

Biome	SST	MLDmax	MLDmin	Wind	Ice
NP ICE	8.04	1.82	2.66	1.34	9.69
NP SPSS	1.23	1.18	1.25	1.20	—
NP STSS	1.63	2.00	1.43	1.79	—
NP STPS	2.55	1.70	1.82	2.26	—
PEQU-W	1.38	3.06	3.33	1.29	—
PEQU-E	3.67	1.53	2.37	4.11	—
SP STPS	1.36	1.12	1.36	1.38	—
NA ICE	9.74	2.14	3.32	1.75	9.58
NA SPSS	1.40	1.81	1.21	1.82	—
NA STSS	1.41	2.06	1.22	1.73	—

NA STPS	2.74	1.32	1.41	2.83	—
AEQU	1.54	1.89	1.45	2.91	—
SA STPS	1.67	1.25	1.63	1.33	—
IND STPS	1.57	1.41	1.14	1.75	—
SO STSS	1.71	1.36	1.68	1.08	—
SO SPSS	1.13	1.28	1.07	1.25	—
SO ICE	3.06	1.24	1.68	1.48	3.97