# Anthropogenic climate change drives non-stationary phytoplankton varianceinternal variability

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**Abstract.** Multiple studies conducted with Earth System Models suggest that anthropogenic climate change will influence marine phytoplankton over the coming century. Light limited regions are projected to become, with light limited regions becoming more productive and nutrient limited regions less productive. Anthropogenic climate change can influence not only the mean state, but also the variance internal variability around the mean state, yet little is known about how variance internal

- 5 variability in marine phytoplankton will change with time. Here, we quantify the influence of anthropogenic climate change on internal variability in marine phytoplankton biomass from 1920 to 2100 using the Community Earth System Model 1 Large Ensemble (CESM1-LE). We find a significant decrease in the internal variance-variability of global phytoplankton carbon biomass under a high emission (RCP8.5) scenario, with heterogeneous regional trends. Decreasing variance internal variability in biomass is most apparent in the subpolar North Atlantic and North Pacific. In these high-latitude regions, zooplankton
- 10 grazing acts as a top-down control in reducing internal variance in phytoplankton biomass, with bottom-up controls (e.g., light, nutrients) having only a small effect on biomass variance. Grazing-driven declines in phytoplankton variance are also apparent in nutrient supply, temperature) influence changes in biomass internal variability. In the biogeochemically critical regions of the Southern Ocean and the Equatorial Pacific-, bottom-up controls (e.g., light, nutrients) and top-down controls (e.g., grazer biomass) affect changes in phytoplankton carbon internal variability, respectively. Our results suggest that climate mitigation
- 15 and adaptation efforts that account for marine phytoplankton changes (e.g., fisheries, <u>marine carbon cycling</u>) should also consider changes in phytoplankton <del>and zooplankton variance internal variability</del> driven by anthropogenic warming, particularly on regional scales.

# 1 Introduction

Anthropogenic climate change has significantly impacted significantly impacts marine ecosystems from phytoplankton (Bopp et al., 2001, 2013; Laufkötter et al., 2015; Kwiatkowski et al., 2020) to fish (Perry et al., 2005; Cheung et al., 2009, 2010; Mills et al., 2013; Wernberg et al., 2016; Flanagan et al., 2018; Staudinger et al., 2019). As the base of the marine food web, phytoplankton

support diverse marine ecosystems by providing food for higher trophic levels (Falkowski, 2012). Constraining future changes in phytoplankton with anthropogenic warming is important at regional scales for fisheries adaptation (Pauly and Christensen, 1995; Chassot et al., 2010; Link and Marshak, 2019; Marshak and Link, 2021), particularly as phytoplankton biomass is incor-

25 porated into offline fisheries models to predict changing catch potential (Christensen and Walters, 2004; Travers-Trolet et al., 2009; Lehodey et al., 2010; Maury, 2010; Blanchard et al., 2012; Christensen et al., 2015; Jennings and Collingridge, 2015; Tittensor et al., 2018; Petrik et al., 2019; Heneghan et al., 2021). In this context, understanding changes in both phytoplankton biomass and its variance internal variability is essential in reducing uncertainty in marine ecosystem projections.

The abundance and distribution of phytoplankton, the base of the marine food web and an important component of the marine

- 30 carbon cycle, will likely change with anthropogenic warming. Future projections of climate change impacts reveal a global loss of marine net primary production (NPP) and phytoplankton biomass, particularly at middle and low latitudes (Steinacher et al., 2010; Bopp et al., 2013; Lotze et al., 2019; Tittensor et al., 2021). A majority of Earth System Models (ESMs) project an increase in phytoplankton abundance in the high latitude ocean as light limitation is alleviated by stratification, increasing temperature stimulates photosynthesis, and sea ice cover declines (Steinacher et al., 2010; Bopp et al., 2013). In contrast, a
- 35 decrease in the low latitude oceans is projected as nutrient limitation from thermal stratification is enhanced (Steinacher et al., 2010; Kwiatkowski et al., 2020). While bottom-up controls (e.g., nutrient flux, light availability) have been shown to affect phytoplankton growth in a changing climate, top-down controls (i.e., zooplankton grazing) also play a role. For example, analysis across a suite of models forced under climate change scenarios revealed reveal grazing pressure as a driver of biomass decline in low to intermediate latitude regions (Laufkötter et al., 2015). Additionally, top-down controls have been shown to
- 40 affect regional changes in NPP and export production (Bopp et al., 2001), as well as the timing of phytoplankton bloom onset (Yamaguchi et al., 2022). Regional redistributions of phytoplankton biomass have consequences for fisheries management and conservation (Blanchard et al., 2017; Stock et al., 2017), and may have implications for economics and policy making decisions (Moore et al., 2021).

While climate change is known to impact the mean state of phytoplankton biomass or NPP (Bopp et al., 2013; Kwiatkowski et al.,

- 45 2020), less is known about how climate change will affect <u>internal</u> variability in these quantities. One recent modeling study found that the climate change alters the timing of seasonal blooms in many regions of the global ocean, an effect that could be realized by the end of the century (Yamaguchi et al., 2022). Several other recent studies have demonstrated how other aspects of the coupled atmosphere-ocean climate system are projected to experience changes in <del>variance internal</del> variability in a changing climate (Resplandy et al., 2015; Landschützer et al., 2018; Kwiatkowski and Orr, 2018; Rodgers et al., 2021).
- For example, Resplandy et al. (2015) examined the contribution of internal variability to air-sea  $pCO_2$  and  $pO_2$  fluxes with climate change using a suite of six ESMs. Their analyses revealed distinct regional differences in internal variability of air-sea  $pCO_2$  and  $pO_2$  fluxes gas fluxes, with the Southern Ocean and the tropical Pacific playing a significant role. Other studies have revealed increases in the frequency of modes of internal variability such as El Niño and La Niña events in response to greenhouse warming (Timmermann et al., 1999; Cai et al., 2014, 2015, 2022). Clarifying how variance internal variability in
- 55 phytoplankton biomass may be changing over long time scales with climate change is important for fisheries management, especially at regional scales, as it affects our ability to make accurate near-term predictions of fisheries production. Near-term

predictions of phytoplankton biomass may also benefit from knowledge of the projected magnitude of internal variability, as the chaotic nature of internal variability hampers near-term predictions (Meehl et al., 2009, 2014).

Here, we quantify changes in the internal variability (ensemble spread) of phytoplankton biomass over the next century using

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a large ensemble of an ESM, in which each ensemble member experiences a different phasing of internal climate variability but is forced with a common emissions scenario. We illustrate the drivers of these changes in variance internal variability via statistical analysis of physical and biogeochemical model output and demonstrate their relative importance in key fisheries regions. While we recognize that an ESM (and indeed, the real world) is a complex, nonlinear system, we approximate at first-order the linear relationships between key variables to attribute drivers of change in phytoplankton biomass variance.

## 65 2 Methods

# 2.1 Community Earth System Model 1 Large Ensemble

## 2.1.1 Model Description

We evaluate changes in phytoplankton biomass variance internal variability using output from the Community Earth System Model 1 Large Ensemble (CESM1-LE) (Kay et al., 2015). CESM1 is a fully-coupled climate model that simulates Earth's

- 70 climate under historical and Representative Concentration Pathway (RCP) 8.5 external forcing by simulating the evolution of coupled atmosphere, ocean, land, and sea ice component models (Hurrell et al., 2013). The ocean physical model is the ocean component of the Community Climate System Model version 4 (Danabasoglu et al., 2012) and has a nominal 1° resolution and 60 vertical levels. The Parallel Ocean Program version 2 (POP2) ocean model consists of an upper-ocean ecological module which incorporates multi-nutrient co-limitation of nitrate, ammonium, phosphate, dissolved iron, and silicate on phytoplankton
- 75 growth and dynamic iron cycling (Moore et al., 2004; Doney et al., 2006; Moore and Braucher, 2008). The Biogeochemical Elemental Cycle (BEC) model simulates three phytoplankton functional types (PFTs): diatoms, diazotrophs, and small phytoplankton (i.e., cyanobacteria, nanophytoplankton, picoeukaryotes). Each PFT plays a unique role in the marine ecosystem and occupies a distinct ecological niche. For example, diatoms grow faster in cool, high-nutrient environments while small phytoplankton thrive in warmer, low-nutrient environments. In contrast, diazotrophs are not limited by nitrogen availability due
- to their ability to biologically fix nitrogen from the atmosphere. Each PFT has a maximum growth rate, which is dictated by temperature (scaled by a temperature function with a Q10 of 2.0), and limited by nutrient and light availability (Moore et al., 2004, 2013). Anthropogenic warming can alter these environmental variables and, in turn, affect phytoplankton abundance and productivity. Photoadaptation (variable chlorophyll to carbon ratios) occurs in response to variations in irradiance and nutrient availability (Geider et al., 1998; Moore et al., 2004). In addition to these bottom-up controls, top-down controls, such
- as zooplankton grazing, can also affect phytoplankton biomass. The ecosystem model simulates a single generic zooplankton functional type (ZFT) with different grazing rates and half saturation constants prescribed for different PFTs (e.g., slower zooplankton grazing rates for larger phytoplankton i.e., diatoms). Grazing rate is computed using a Holling Type III (sigmoidal) relationship and is a function of both prey density and temperature (Figure S1, Equation 5). Zooplankton loss is a function of

a linear mortality term which represents natural mortality and a non-linear predation term which represents losses from preda-

90 tion. Both of these loss terms scale with temperature. While zooplankton growth and loss terms both scale with temperature, a non-linear parameterization of the loss term results in a relatively larger increase in loss than increase in production with warming.

Large ensembles of ESMs are a recently developed research tool which allow us to disentangle fluctuations due to internal climate variability from those imposed by externally forced anthropogenic trends. Internal variability refers to variability in

- 95 the climate system which occurs in the absence of external forcing, and includes processes related to the coupled oceanatmosphere system (e.g., El Niño Southern Oscillation, Pacific Decadal Oscillation) (Santer et al., 2011; Deser et al., 2010; Meehl et al., 2013). In contrast, external forcing refers to the signal imposed by processes external to the climate system, such as solar variability, volcanic eruptions, and rising greenhouse gases from fossil fuel combustion (Deser et al., 2012, 2010; Schneider and Deser, 2018). The CESM1-LE simulates the evolution of the climate system with multiple ensemble members,
- 100 each initiated with slightly different atmospheric temperature fields and branched from a multi-century 1850 control simulation with constant pre-industrial forcing (Lamarque et al., 2010; Danabasoglu et al., 2012). Once the control simulation achieved equilibrium with the 1850 forcing, ensemble members were integrated The CESM1-LE simulates the evolution of the climate system from 1920 to 2100 using round-off level differences in the initial air temperature field (Kay et al., 2015), resulting in each ensemble member experiencing a different evolution with multiple ensemble members, each expressing a different
- 105 phasing of internal climate variability (e. g., each member has different phasing of climate modes such as El Niño Southern Oscillation). while responding to a shared external forcing prescription (Kay et al., 2015). Variable phasing of internal climate variability (e.g., ENSO) across ensemble members can influence phytoplankton biomass variability through the propagation of physical climate variability to biologically relevant environmental variables. For example, an ensemble member with a positive phasing of ENSO may display decreased phytoplankton biomass in the Eastern Equatorial Pacific due to decreased upwelling
- 110 nutrient flux. RCP8.5 forcing was applied from 2006 to 2100 (Meinshausen et al., 2011) with well-mixed greenhouse gases and short-lived aerosols projected by four different Integrated Assessment Models (Lamarque et al., 2010). A total of 40 ensemble members were generated for the CESM1-LE experiment. Six CESM1-LE members had corrupted ocean biogeochemistry, therefore, we use the 34 CESM1-LE members with valid ocean biogeochemistry.

#### 2.1.2 Statistical Analysis of Model Output

- 115 Analyses were conducted using annual mean output at 1° resolution from 1920 to 2100. Changes in CESM1 phytoplankton variance\_internal variability can be assessed via statistical analysis of chlorophyll concentration, net primary productivity (NPP), or phytoplankton carbon concentration (an indicator of total biomass). In our analysis we focus on biomass (phytoplankton carbon concentration) because it is an important predictor variable in offline fisheries models (Christensen and Walters, 2004; Travers-Trolet et al., 2009; Lehodey et al., 2010; Maury, 2010; Blanchard et al., 2012; Christensen et al., 2015; Jennings and Colling
- 120 2015; Tittensor et al., 2018). Additionally, under climate change scenarios, phytoplankton biomass may be a more reliable indicator than NPP of climate change impacts (Bopp et al., 2021). Vertical integrals (top 150m) of biomass carbon concentration from each PFT were calculated and then summed to create maps of total phytoplankton biomass.

**Figure 1.** Comparison between observed and modeled phytoplankton biomass interannual variability. (a) Temporal standard deviation in annual mean phytoplankton carbon concentration  $(\underline{mg m}^{-3})$  reconstructed from remotely sensed chlorophyll concentrations, backscattering coefficients, and phytoplankton absorption (1998 to 2019) (Bellacicco et al., 2020). (b) Temporal standard deviation in annual mean phytoplankton carbon concentration  $(\underline{mg m}^{-3})$  simulated by ensemble member 1 of the CESM1-LE over the same observational period (1998 to 2019). Note the different magnitudes on the colorbars.

We classified the marine environment into 11 ecologically cohesive biomes as in Tagliabue et al. (2021) and Vichi et al. (2011) (Figure S2), which are a consolidation of the 38 ecological regions defined in Longhurst (2007). The provinces were aggregated

- 125 using multivariate statistical analysis (Vichi et al., 2011). of physical (i.e., salinity, temperature, mixed layer depth) and biological (i.e., chlorophyll concentration) ocean parameters to group ocean regions with similar physical and environmental conditions (Vichi et al., 2011). The ocean provinces were defined by randomly selecting from a combination of model and observational datasets and testing for statistical significance using analysis of similarities (ANOSIM) (Vichi et al., 2011). Although we consider all 11 biomes in our analysis, we analyze drivers in four biomes that are particularly relevant for fisheries production
- 130 and/or of high biogeochemical interest: the subpolar Atlantic (ASP), the subarctic Pacific (SAP), the Equatorial Pacific (EQP), and the Southern Ocean (SOC) (Figure S2). ASP is a consolidation of aggregated biogeochemical provinces 4, 11, and 15, SAP a consolidation of 50 and 51, EQP a consolidation of 61, 62, and 63, and SOC a consolidation of 21, 81, 82, and 83 (Longhurst, 2007; Vichi et al., 2011) (Figure S2). Important biogeochemical regions are those characterized by coherent physical and environmental conditions, which support unique marine ecosystems and play an outsized role on global ocean
- 135 biogeochemistry.

Internal variability at each location (x, y) is approximated as the standard deviation  $(\sigma)$  across ensemble members (EMs) at a given time (t),

$$\sigma(x, y, t) = \sigma(EM(x, y, t)). \tag{1}$$

The coefficient of variation (CoV) is calculated as the standard deviation across the ensemble members divided by the ensemble 140 mean.

$$\underbrace{CoV}_{(x,y,t)} = \frac{\sigma(EM(x,y,t))}{\overline{LE}^{EM}}.$$
(2)

The forced response of the large ensemble is calculated as the mean of ensemble members at a given location and time,

$$\overline{LE}(x,y,t) = \frac{\sum_{1}^{n} EM(x,y,t)}{n},$$
(3)

where n is the number of ensemble members.

- 145 We quantified the drivers of phytoplankton carbon biomass CoV in key ocean regions by generating an ensemble of boosted regression trees. Unlike linear models, boosted trees are able to capture non-linear interaction between the predictors and the response. A regression tree ensemble is a predictive model composed of a weighted combination of multiple regression trees. At every step, the ensemble fits a new learner to the difference between the observed response and the aggregated prediction of all learners grown previously, aiming to minimize mean-squared error. We generate an ensemble of boosted regression trees
- 150 (maximum tree depth = 10) using the Matlab function *fitrensemble*. Our predictor variables are the regional mean, ensemble mean temperature, mixed layer depth, incoming shortwave radiation, physically mediated iron, physically mediated phosphate, zooplankton carbon, and zooplankton grazing (diatom, small phytoplankton, or their sum), while our response variable is CoV of phytoplankton carbon (diatom, small phytoplankton, or their sum) annually resolved from 2006 to 2100. We use the Matlab function *predictorImportance* to estimate the importance of the predictors for each tree learner in the ensemble; it computes
- 155 the importance of the predictors in a tree by summing changes due to splits on every predictor and dividing the sum by the total number of branches.

## 2.2 Model Evaluation

We used remotely sensed estimates of phytoplankton carbon to evaluate the representation of phytoplankton interannual variability in the CESM1-LE. In other words, we evaluate the temporal variability in modeled phytoplankton biomass from year to

- 160 year. We note that this interannual variability is different than the internal variability (ensemble spread) that we discuss at length in this study, but is nevertheless a target for model validation. Although phytoplankton carbon concentrations cannot be measured directly by satellites, they can be reconstructed using algorithms that incorporate remotely sensed chlorophyll concentrations, detrital backscattering coefficients, and phytoplankton absorption (Kostadinov et al., 2016; Martinez-Vicente et al., 2017; Roy et al., 2017; Sathyendranath et al., 2020; Brewin et al., 2021). We use the observational phytoplankton carbon dataset of
- 165 Bellacicco et al. (2020), annually averaged and interpolated onto a 1° grid, to evaluate temporal interannual variability in phytoplankton biomass in a single model ensemble member. Figure 1a shows satellite derived estimates of interannual variability in phytoplankton carbon with regions of relatively low phytoplankton variability shown in light green-yellow and regions of relatively high variability in dark bluepurple. Remotely sensed observations capture areas of high interannual variability in the subpolar North Atlantic, North Pacific, and Southern Ocean and areas of low interannual variability in the subtropical gyre
- 170 regions. Similar spatial patterns are apparent when compared to the range of phytoplankton interannual variability in ensemble member 1 of the CESM1-LE over the observational period (1998 to 2019) (Figure 1b). However, while the model ensemble captures regional patterns of observed variability, the CESM1-LE overestimates the magnitude of observed interannual variability. As such, estimates of interannual variability derived from the model ensemble will tend to overestimate that observed in the real worldSome regions of the global ocean display a substantial mismatch in interannual variability between the model
- 175 and that estimated from observations (Figure 1, Table S1). While the differences can be quite large in some regions, we note that this is an evaluation of interannual variability (rather than internal variability, the focus of this study), and that estimates from the satellite product derive from a collection of data products which may also display biases (Table S1).

**Figure 2.** (a) Global change in annual mean total phytoplankton carbon concentration simulated by the CESM1-LE in mmol C m<sup>-2</sup> from the historical period through the RCP8.5 forcing scenario (1920 to 2100). The ensemble mean is shown in the black curve and the 34 individual ensemble members are shown in the gray curves. (b) Global change in the coefficient of <u>variance variation</u> in annual mean total phytoplankton carbon concentration over the same period, smoothed using a 5 year window. Trend in the coefficient of <u>variance variation</u> over the RCP8.5 forcing scenario is shown in the black dashed line.

As an evaluation of the model's ability to represent internal variability (ensemble spread), we compare the internal variance variability in chlorophyll simulated in the CESM1-LE to a synthetic ensemble generated from observed <u>surface</u> chlorophyll concentrations over the MODIS remote sensing record (Elsworth et al., 2020, 2021) (Figure \$2\$3; chlorophyll was readily available in the CESM1-LE and can be directly compared with our synthetic ensemble of observed <u>surface</u> chlorophyll). A synthetic ensemble is a novel-technique that allows the observational record to be statistically emulated to create multiple possible evolutions of the observed record, each with a unique sampling of internal climate variability (McKinnon et al., 2017; McKinnon and Deser, 2018). Compared to the internal variability over the observational period (2002 to 2020) (purple circle, (Figure \$2\$3), the model ensemble slightly overestimates the magnitude of internal variability in chlorophyll observed in the

real world.

Taken together, our model validation exercises demonstrate that the model tends to overestimate both the temporal (interannual) variability and the internal variability in phytoplankton, as compared to satellite observations on both global and regional scales. Thus, we must interpret our findings with this caveat in mind.

## 190 3 Results

200 Atlantic subpolar gyre, the phytoplankton biomass declines by 40-50% of its mean (Figures 3a, S3a), likely due to weakening of the Atlantic Meridional Overturning Circulation (AMOC) and the subsequent disruption of nutrient flux (Brander, 2010) S4a). This result is consistent with previous modelling studies which identified a 50% reduction in North Atlantic primary production associated with AMOC weakening during the last glacial period (Schmittner, 2005). A weakening of the AMOC is also projected with anthropogenic warming (Manabe and Ronald, 1993; Stocker and Schmittner, 1997).

**Figure 3.** (a) Percentage change in annual total phytoplankton carbon concentration over the RCP8.5 forcing scenario (2006 to 2100) simulated by the CESM1-LE. (b) Percentage change in annual total phytoplankton internal variability over the same period. The change in the mean and the variability are calculated using averages across the first (2006 to 2016) and last (2090 to 2100) decades of the RCP8.5 forcing scenario. Hatched areas indicate regions of trend insignificance determined by a t-test with a p value greater than 0.05. Summary statistics for the t-test are available in the supplemental information (Table S2).

- Regional changes in phytoplankton biomass are dominated by changes in diatom and small phytoplankton (Table 1). We aggregate biomass across 11 ecological provinces (Vichi et al., 2011; Tagliabue et al., 2021), and present changes in total and PFT biomass over the RCP8.5 scenario in Table 1. The CESM1-LE simulates the largest decline in total phytoplankton carbon concentration in the Atlantic subpolar (ASP) region, where diatom biomass declines by  $\sim$ 80 mmol C m<sup>-2</sup>, and small phytoplankton biomass increases slightly ( $\sim$ 8 mmol C m<sup>-2</sup>). We observe moderate decreases in the subpolar Pacific (SAP)
- 210 region that are again driven by declines in diatom carbon concentration, with minor contributions from changes in small phytoplankton carbon concentration (Table 1). The CESM1-LE simulates a smaller decline in total carbon concentration in the Equatorial Pacific (EQP) region, where diatom biomass declines  $\sim$ 7 mmol C m<sup>-2</sup> and small phytoplankton biomass declines  $\sim$ 5 mmol C m<sup>-2</sup>. The smallest decline in total carbon concentration occurs in the South Pacific subtropical gyre (SPS) region, where diatom biomass declines  $\sim$ 4.3 mmol C m<sup>-2</sup> and small phytoplankton biomass declines  $\sim$ 4.6 mmol C m<sup>-2</sup>.
- 215 Internal variability in global phytoplankton biomass, which is indicated by the spread across the individual ensemble members (gray lines; Figure 2a), declines over the RCP8.5 forcing period from 2006 to 2100. To quantify how the range of internal variability in phytoplankton biomass is changing with anthropogenic warming, we calculated the coefficient of variance variation as the standard deviation across the ensemble members for a given year (ensemble spread) divided by the ensemble mean. Figure 2b illustrates the change in the coefficient of variance variation from the historical period through the RCP8.5 forcing scenario (1920 to 2100). The coefficient of variance variation is relatively constant across the historical period (1920).
- to 2005), and then significantly declines by  $\sim 20\%$  from 2006-2100.

A decrease in global phytoplankton internal variability with anthropogenic warming is not unique to the CESM1-LE. We illustrate this by analyzing <u>surface</u> phytoplankton chlorophyll (rather than biomass; <u>surface</u> chlorophyll was readily available in the CMIP5 archive) from three other CMIP5 ESM large ensembles which include representation of ocean biogeochemistry: the GFDL-ESM2M from the Geophysical Fluid Dynamics Laboratory (GFDL; Dunne et al., 2012, 2013), the CanESM2 from the Canadian Centre for Climate Modelling and Analysis (Christian et al., 2010; Arora et al., 2011), and the MPI-ESM-LR from the Max Planck Institute (MPI; Giorgetta et al., 2013; Ilyina et al., 2013), consisting of 30, 50, and 100 ensemble members, respectively. Similarly to the CESM1-LE, historical forcing was applied through 2005, followed by RCP8.5 forcing through 2100. While there is substantial spread in the mean coefficient of variance-variation across the four models, a similar decline in the coefficient of variance-variation can be observed across each of the four ESM ensembles, (Figure \$2\$, From 2006 to 2100, the coefficient of variance-variation decreases by  $3.3 \times 10^{-5}$  yr<sup>-1</sup> in the CESM1-LE,  $2.0 \times 10^{-4}$  yr<sup>-1</sup> in the MPI-ESM-

LR1,  $5.2 \times 10^{-5}$  yr<sup>-1</sup> in the CanESM2, and  $3.9 \times 10^{-4}$  yr<sup>-1</sup> in the GFDL-ESM2M. The change in the coefficient of variation

#### is calculated using averages across the first (2006 to 2016) and last (2090 to 2100) decades of the RCP8.5 forcing scenario.

These declines are statistically significant in all model ensembles with the exception of the MPI-ESM-LR1 (Figure S2S3).

- In comparison to the mean change in phytoplankton biomass, changes in phytoplankton internal variability with time are spatially more heterogeneous across the global ocean (Figure 3b). The largest decreases in variance internal variability are apparent in the North Atlantic and North Pacific subpolar regions (on the order of 50-70% of the mean biomass variance internal variability), with smaller declines in the Equatorial Pacific and Southern Oceans (on the order of 30-50% of the mean biomass variance internal variability) (Figure 3b, S3S4b). Changes in variance internal variability in the subtropical regions are charac-
- 240 terized by mixed trends, with areas of both increasing and decreasing variance internal variability across the RCP8.5 forcing scenario (Figure 3b, \$3\$4b).

Global changes in total phytoplankton biomass variance standard deviation are a manifestation of changes in diatom and small phytoplankton variability (Table 1). We observe the largest magnitude decline in total phytoplankton carbon variance standard deviation in the subpolar Atlantic (ASP) region, where diatom variance standard deviation declines by  $\sim 10$  mmol C

m<sup>-2</sup> and small phytoplankton variance standard deviation declines by ~2 mmol C m<sup>-2</sup> (Table 1). The CESM1-LE simulates a moderate magnitude decline in total phytoplankton variance standard deviation in the subarctic Pacific (SAP) region, driven by a decrease in small phytoplankton variance standard deviation (~2 mmol C m<sup>-2</sup>) with minor contributions from declines in diatom variance standard deviation (~1 mmol C m<sup>-2</sup>) (Table 1). Moderate declines in variance standard deviation are also simulated in the Arctic (ARC), North Atlantic subtropical gyre (NAS), Southern Ocean (SOC), and Equatorial Pacific (EQP)
regions, driven by declines in diatom carbon variance standard deviation in the SOC region and declines in small phytoplankton variance internal variability in the EOP region (Table 1).

**Table 1.** Changes in phytoplankton biomass and its <u>internal</u> variability in the CESM1-LE from 2006 to 2100 for the 11 ecological provinces defined in Vichi et al. (2011) and Tagliabue et al. (2021). Units are mmol C  $m^{-2}$ . The change in the mean and standard deviation are

calculated using averages across the first (2006 to 2016) and last (2090 to 2100) decades of the RCP8.5 forcing scenario.

Region		Change in Mean			Change in Standard Deviation		
Biome	Name	Total	Diatom	Small	Total	Diatom	Small
ARC	Arctic	-21	-58	+37	-1.4	-2.8	-0.3
ASP	Atlantic subpolar	-71	-79	+8.2	-5.6	-9.9	-2.2
NAS	North Atlantic subtropical gyre	-18	-15	-2.9	-1.8	-2.8	-0.3
EQA	Equatorial Atlantic	-12	-6.6	-5.9	-0.1	-0.4	+0.2
SAS	South Atlantic subtropical gyre	-10	-7.2	-3.1	-0.5	-0.6	-0.1
IND	Indian Ocean	-11	-6.1	-4.7	+0.1	0	+0.1
SAP	subarctic Pacific	-21	-15	-5.4	-0.1	-1.4	-2.4
NPS	North Pacific subtropical gyre	-11	-5.6	-4.9	-0.2	-0.4	+0.1
EQP	Equatorial Pacific	-12	-6.6	-5.0	-2.0	-2.0	-0.2
SPS	South Pacific subtropical gyre	-8.9	-4.3	-4.6	-0.1	0	-0.1
SOC	Southern Ocean	-9.3	-2.8	-6.6	-1.0	0	-1.3

**Figure 4.** Distribution of the dominant phytoplankton functional type in biomass carbon averaged over across the RCP8.5 forcing scenario (2006 to 2100. 2100). The CESM1-LE simulates three phytoplankton functional types: diatoms, diazotrophs, and small phytoplankton. Regions where diatoms dominate are shown in yellow, regions where diazotrophs dominate are shown in pink, and regions where small phytoplankton dominate are shown in purple. Diazotrophs do not dominate in any region of the global ocean. The four ecological provinces are shown: subpolar Pacific (SAP), subpolar Atlantic (ASP), Equatorial Pacific (EQP), and Southern Ocean (SOC).

To guide our attribution analysis of changing phytoplankton biomass and its internal variability, we considered the dominant ecological assemblage across different regions of the global ocean. The CESM1-LE simulates three phytoplankton functional types, each of which thrive in distinct regions of the global ocean. Diatoms dominate in the subpolar Atlantic and Pacific, the Eastern Equatorial upwelling zone, and portions of the Southern Ocean, while small phytoplankton dominate across the subtropical gyres and portions of the Southern Ocean (Figure ??.4). In contrast, diazotrophs, a minor contributor to total carbon biomass, are present at such low concentrations that they do not dominate anywhere in the global ocean (Figure ??.4). Using the ecologically cohesive regions defined by Tagliabue et al. (2021) and Vichi et al. (2011), we selected areas that align with the most productive fisheries regions by catch in the Atlantic and Pacific basins (FAO, 2020), as well as regions of global biogeochemical importance for further analysis. In each ecological region we identified the dominant phytoplankton functional type to include in our driver analysis. In regions where multiple phytoplankton functional types dominated, we used total carbon concentrations to reflect the mixed ecological assemblage.

We quantified the relationship between phytoplankton carbon and the variables which contribute to changing phytoplankton biomass and its internal variability by performing a multiple linear regression (MLR) analysis. The MLR analysis was performed on linearly detrended annual anomalies using the ordinary least squares function of the Python package statsmodels.api. We then reconstructed the contribution of each driver variable to phytoplankton biomass and its internal variance between the beginning of the century (2006 to 2016) and the end of the century (2090 to 2100) by multiplying the MLR regression coefficients by the 10-year averaged mean and standard deviation across the model ensemble (ensemble spread), respectively, for each variable. We reconstruct mean phytoplankton biomass ( $\overline{C_{phyto}}$ ) and its variance ( $\sigma_{C_{phyto}}$ ) as a function of light (*Solar*), temperature (*SST*), phosphate advection (*Nutrient*), mixed layer depth (*MLD*), and zooplankton grazing (*Grazing*),

$$\overline{C_{phyto}} = \frac{\partial C_{phyto}}{\partial Solar} \overline{Solar} + \frac{\partial C_{phyto}}{\partial SST} \overline{SST} + \frac{\partial C_{phyto}}{\partial Nutrient} \overline{Nutrient} + \frac{\partial C_{phyto}}{\partial MLD} \overline{MLD} + \frac{\partial C_{phyto}}{\partial Grazing} \overline{Grazing} \overline{Graz$$

and,

$$\sigma_{C_{phyto}} = \frac{\partial C_{phyto}}{\partial Solar} \sigma_{Solar} + \frac{\partial C_{phyto}}{\partial SST} \sigma_{SST} + \frac{\partial C_{phyto}}{\partial Nutrient} \sigma_{Nutrient} + \frac{\partial C_{phyto}}{\partial MLD} \sigma_{MLD} + \frac{\partial C_{phyto}}{\partial Grazing} \sigma_{Grazing},$$

- 275 where  $\overline{X}$  represents the 10-year ensemble mean for a particular variable over a given period,  $\sigma_X$ -represents the standard deviation across all ensemble members for a particular variable and  $\frac{\partial C_{phyto}}{\partial X}$  represents the MLR regression coefficient describing the relationship between a particular variable and phytoplankton biomass. We approximate at first-order the linear relationships between variables and do not account for second-order (co-variance among explanatory variables) relationships in our statistical method; these terms do not contribute much to the total change in mean (Figure **??**a) and variance (Figure **??**b).
- We identify the drivers of identify the importance of different predictors to changing phytoplankton biomass and its internal variance CoV in four distinct ecological regions using our statistical a machine learning (boosted regression tree) approach. In the subpolar Atlantic (ASP) and subpolar Pacific (SAP) ecological provinces , where diatoms dominate total biomass, the mean decline in diatom carbon is associated with a decrease in diatom grazing (Figure ??a)and a decrease zooplankton carbon, respectively (Figure ??b). In the ASP and SAP ecological provinces (Figure ??), diatom variance 4), diatom biomass CoV
   declines between the beginning and end of the century (Figure 5a, b, Table 1). In both provinces, the largest contributions to
- this decline in diatom variability derive from a decline in diatom grazing variability, while more minor contributions derive from bottom-up controls such as solar fluxthe Atlantic subpolar region, the most important predictor of diatom biomass CoV is phosphate advection, with smaller contributions from zooplankton carbon (Figure 5a). In the subarctic Pacific region, sea surface temperature , nutrient advection , and mixed layer depth is the most important predictor of diatom biomass CoV, with
  290 phosphate advection playing a secondary role (Figure 5a, b).
  - As the Southern Ocean (SOC) and Equatorial Pacific (EQP) <u>ecological</u> provinces are characterized by mixed phytoplankton assemblages where both diatoms and small phytoplankton dominate (Figure 4), we identify the drivers of the change in total phytoplankton mean and variance here. The mean decline in total carbon in the SOC province are dominated by a decrease zooplankton grazing (Figure ??e). In contrast, drivers of the mean decline in total carbon in the EQP province include a
- 295 combination of zooplankton carbon, diatom grazing, and small phytoplankton grazing (Figure ??d).In contrast to the ASP and SAP predictors of total phytoplankton CoV here. In contrast to the subpolar Atlantic and subpolar Pacific provinces, we observe a relatively smaller decline in internal phytoplankton variance phytoplankton CoV between the beginning and end of the century in the Southern ocean (Figure 5e). Similarly to ASP and SAP provinces, the largest contributions to the change in internal variability derive from a decline in grazing variability, with bottom-up controls playing only a small role Ocean.
- 300 (Table 1). The most important predictors of phytoplankton CoV in the Southern Ocean (SOC) region derive from solar flux, with more minor contributions from iron and phosphate advection (Figure 5c). In the Equatorial Pacific , total phytoplankton variance declines between the beginning and end of the century, with the largest contributions to this decline deriving from zooplankton carbon and diatom grazing, with increasing variance in small phytoplankton grazing region, zooplankton carbon is the most important predictor of total phytoplankton CoV, while iron and phosphate advection play less of a predictive role
- 305 (Figure 5d).

We explore the sensitivity of our results in relation to the functional form of grazing in the CESM1-LE (Figure S4). A eaveat to our statistical approach is our assumption that the regression coefficients are constant across the century while the variance is changing. In our model, the sensitivity of grazing rate to prey concentration can be affected by changes in prey concentration and changes in temperature (Figure S1), both of which are modified in a changing climate. We test the robustness

**Figure 5.** Reconstructed changes in the contribution Relative importance of each driver variable to predictor variables on phytoplankton biomass variance coefficient of variation across the RCP8.5 forcing scenario (2006 to 2100) with the beginning of the century shown in light blue and the end of the century shown in dark blue. Marine ecological regions are defined in Tagliabue et al. (2021). Regions were selected which aligned with the highest fisheries catch in the (a) Atlantic and (b) Pacific basins and the biogeochemically important (c) Southern Ocean and (d) Equatorial Pacific regions. The dominant phytoplankton functional type is considered in each region. In regions with a mixed ecological assemblage, total phytoplankton carbon is considered.

310 of our assumption in the two key fisheries regions by performing another MLR to reconstruct drivers of diatom variance with different regression coefficients between the beginning and end of the century (Figure S1, Figure S4). While the contribution of zooplankton grazing to the change in diatom variance changes slightly with this new approach, the results are similar.

Our analysis reveals that changes in grazer variance dominate the change in phytoplankton variance over the next century, so we next deconvolve the changes in grazer variance into its two drivers, prey concentration (phytoplankton biomass) and

- 315 temperature (Figure S1) using a similar MLR approach as for phytoplankton biomass variance (In all four ecological provinces, a combination of bottom-up controls (e.g., nutrient supply, light availability) and top-down controls (e.g., Equation 4). The results of this deconvolution (Figure ??) demonstrate that the changing grazing variance is driven primarily by changing phytoplankton biomass variance, with only small contributions from changing temperature variance. Thus, it is not possible to cleanly separate cause and effect in this non-linear, coupled system: phytoplankton variance changes because grazer variance
- 320 changes, and grazer variance changes because phytoplankton variance changes. Nevertheless, our results suggest that both phytoplankton and zooplankton experience declines in variance by the end of the century, and as both are sources of energy for higher trophic levels, this implies that fishery productivity variance will also decline by the end of the centurygrazer biomass) predict the decline in phytoplankton biomass CoV with anthropogenic warming. Our statistical analysis reveals that phosphate advection is an important predictor in the high-latitude regions of both the subpolar Atlantic and Pacific, with sea surface
- 325 temperature playing an important role in the subpolar Pacific. However, in the Southern Ocean and the Equatorial Pacific, solar flux and grazer biomass dominate the predictive skill in phytoplankton biomass CoV.

## 4 Conclusions and Discussion

We quantify both global and regional changes in phytoplankton internal variance variability across the RCP8.5, or businessas-usual forcing scenario in the CESM1-LE. We observe a global decline in phytoplankton variance internal variability in the model ensemble, which is reflected in similar declines in phytoplankton variance internal variability across a suite of CMIP5 models (Figure <u>\$2</u>\$3). Regional changes in phytoplankton variability with anthropogenic climate change in the model ensemble are spatially heterogeneous, with highly productive fisheries regions and important global biogeochemical regions experiencing large changes in variance. Statistical analysis of these specific regions reveal zooplankton grazing (internal variability. Using a machine learning approach, we identify the importance of different predictors to changing phytoplankton

335 biomass internal variability. In all four ecological provinces, a combination of bottom-up controls (e.g., nutrient supply, light

availability) and top-down control) as an important contributor to changes in phytoplankton variance, consistent with previous studies (Bopp et al., 2001; Laufkötter et al., 2015) controls (e.g., grazer biomass) predict the decline in phytoplankton biomass CoV with anthropogenic warming.

While the CESM1-LE represents regional patterns the overall spatial pattern of observed interannual variability in phytoplankton carbon, the model ensemble tends to slightly overestimate overestimates the magnitude of observed internal variance 340 in phytoplankton chlorophyll. As such, the magnitude of changes in phytoplankton internal variance derived from the model ensemble should be interpreted as an overestimate when considering changes in phytoplankton internal variance driven by anthropogenic warming, interannual and internal variability in phytoplankton on regional scales. This caveat is particularly important to consider when interpreting projections from offline fisheries models in the context of fisheries adaptation and planning in a warming climate.

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Our statistical analysis approach has inherent limitations, especially in the context of a attributing drivers changes in an inherently non-linear, coupled system (i.e., reconstructing linear relationships between co-varying variables one in which predictor variables co-vary). In a coupled system such as this, it is difficult to definitively identify cause and effect. In this context, the statistical method can be used as an effective tool to provide a first-order approximation of drivers of phytoplankton variance across the century contributions to changing phytoplankton CoV.

While many studies attribute bottom-up controls to changing phytoplankton with anthropogenic warming (Steinacher et al., 2010; Bopp et al., 2013; Lotze et al., 2019; Tittensor et al., 2021), top-down controls may also play an important role, particularly in our understanding of changing phytoplankton biomass and its variance internal variability. Our study demonstrates a key role for top-down controls on changing phytoplankton biomass and its variance connection between phytoplankton internal

- 355 variability and zooplankton carbon in the subpolar North Atlantic and subpolar North Pacific and Equatorial Pacific. Previous studies of phytoplankton change with climatic warming have demonstrated that grazing pressure is a driver of contributor to biomass decline in low to intermediate latitude regions across a suite of model simulations with different marine ecosystem models (Laufkötter et al., 2015) and that top-down controls can affect regional changes in NPP and export production (Bopp et al., 2001) and is a driver of contributor to future shifts in bloom timing (Yamaguchi et al., 2022) (Yamaguchi et al., 2022)
- 360 ). While grazing pressure has been shown to increase in response to climate change, several ecosystem models have also identified zooplankton grazing as a dominant driver of contributor to phytoplankton assemblage succession during blooms (Hashioka et al., 2012; Prowe et al., 2012a). Additionally, top-down controls have also been observed to affect the onset of the spring bloom (Behrenfeld, 2010; Behrenfeld et al., 2013), to influence primary production in a trait-based ecosystem model (Prowe et al., 2012b).
- The relative simplicity of the ocean biogeochemical ecosystem model in CESM1 (e.g., representation of a single zooplankton 365 functional type with multiple grazing rates) may limit a more detailed evaluation of changing grazing pressures with climate change. While the recent parameterization of the biogeochemical ecosystem model in CESM2 (MARBL) includes similar representation of three PFTs and a single adaptive ZFT (Long et al., 2021), more complex configurations of MARBL include explicit representation of additional PFTs such as coccolithophores (Krumhardt et al., 2019) and ZFTs. Using more complex
- ecosystem models, additional insights into drivers of Additional insights into contributions to internal variability may be gained 370

using our statistical approachmore complex models. Additionally, the use of an ecosystem model of higher complexity may provide more realistic projections of the marine ecosystem with climate change considering change in phytoplankton and zooplankton species diversity with anthropogenic warming (Benedetti et al., 2021). However, our regional analyses suggest that zooplankton grazing pressure should be considered as an important driver of changes in phytoplankton biomass and its

#### 375 variance with anthropogenic warming.

The magnitude and direction of regional changes in phytoplankton variance internal variability are an essential constraint for near-term (subseasonal to decadal) predictions of the local marine ecosystem, particularly in important fisheries regions such as the subpolar Atlantic (ASP) and the subpolar Pacific (SAP) ecological provinces (FAO, 2020). Accurate near-term predictions require foreknowledge of both internal climate variability and external climate change signals. On subseasonal to decadal

- 380 timescales, the magnitude of internal climate variability is often stronger than forced climate change signals (Meehl et al., 2009, 2014). In this context, a decline in phytoplankton internal variance-variability with anthropogenic climate change may improve the accuracy of near-term predictions of phytoplankton biomass, producing more reliable forecasts of fisheries productivity and marine carbon cycling. Future work can utilize these constraints on phytoplankton variance internal variability, particularly on regional scales, to inform climate mitigation and adaptation efforts.
- 385 *Data availability.* CESM1-LE output is available from the Earth System Grid at http://www.cesm.ucar.edu/projects/community-projects /LENS/data-sets.html.

*Author contributions.* GE and NL conceptualized the study. GE analyzed simulation results and prepared the manuscript. N.L. assisted in preparing the manuscript. KK assisted in analysis of simulation results. TM, KK, and SS assisted in reviewing the manuscript.

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## 635 Supplemental information

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In our discussion of zooplankton grazing as a driver of changing phytoplankton variance contributor to changing phytoplankton internal variability with anthropogenic warming, we consider the parameterization of zooplankton grazing in the CESM1-LE. The biogeochemical ecosystem model simulates a single generic zooplankton functional type (ZFT) with different grazing rates and half saturation constants prescribed for different PFTs (e.g. slower zooplankton grazing rates for larger phytoplankton). Grazing rate for the single ZFT is computed using a Holling Type III (sigmoidal) relationship:

$$G = g_{max} \cdot T_{lim} \cdot Z \cdot \frac{P^2}{P^2 + K^2} \tag{4}$$

where  $g_{max}$  is the maximum grazing rate,  $T_{lim}$  is the temperature limitation (Q10) function, Z is the zooplankton concentration, P is the phytoplankton concentration, and K is the half-saturation constant for grazing. Zooplankton loss scales with temperature and a linear mortality term which represents zooplankton losses from predation.

**Figure S1.** Holling Type III (sigmoidal) functional parameterization of zooplankton grazing rate in the biogeochemical ecosystem model of the CESM1-LE across a range of temperatures. Changes in diatom concentration between the beginning and end of the century (BOC and EOC, respectively) are shown in the dark and light orange circles, respectively, with the changes in the ASP region shown above and changes in the SAP region shown below.

Figure S1 illustrates changes in grazing rate as a function of diatom concentration using this parameterization. To approximate the effects of climatic warming, we plot the relationship for across a series of increasing temperatures: (blue)  $5^{\circ}$ C, (orange)  $10^{\circ}$ C, and (green)  $15^{\circ}$ C. The maximum grazing rate increases with warming temperatures. Changes in diatom concentration in mmol m<sup>-3</sup> between the beginning and end of the century are denoted by dark and light orange circles, respectively.

Figure S2. Holling Type III (sigmoidal) functional parameterization of zooplankton grazing rate The 11 ocean ecological provinces defined in the biogeochemical ecosystem model of the CESM1-LE across a range of temperatures. Changes in diatom concentration between the beginning Tagliabue et al. (2021) and end-Vichi et al. (2011). Provinces were aggregated using multivariate statistical analysis of the century physical (BOC and EOCi.e., respectivelysalinity, temperature, mixed layer depth) are shown in the dark and light orange circlesbiological (i.e., respectively, chlorophyll concentration) ocean parameters to group ocean regions with the changes in the ASP region shown above similar physical and ehanges in the SAP region shown belowenvironmental conditions. Figure adapted from Tagliabue et al. (2021). **Table S1.** The temporal standard deviation of phytoplankton biomass ( $\sigma_{temporal}$ ) for ensemble member 1 of the CESM1-LE and the satellite observations from 1998 to 2019 averaged across the 11 ecological provinces defined in Vichi et al. (2011) and Tagliabue et al. (2021). Units are mg C m<sup>-3</sup>.

Biome	Name	$\sigma_{temporal}, model$	$\underbrace{\sigma_{temporal},obs}$
ARC	Arctic	2.7	4.5
ASP	Atlantic subpolar	<u>9.7</u>	4.1
NAS	North Atlantic subtropical gyre	2.8	1.7
EQA	Equatorial Atlantic	1.3	1.4
SAS	South Atlantic subtropical gyre	1.1	1.2
IND	Indian Ocean	0.81	2.0
SAP	subarctic Pacific	3.7	<u>4.0</u>
<u>NPS</u>	North Pacific subtropical gyre	0.85	1.5
EQP	Equatorial Pacific	5.8	1.8
<u>SPS</u>	South Pacific subtropical gyre	0.60	0.93
SOC	Southern Ocean	2.7	2.7

**Figure S3.** Coefficient of variance variation (internal standard deviation divided by ensemble mean) in annual mean global surface ocean chlorophyll concentration from 2006 to 2100 across a suite of CMIP5 model ensembles: (a) (pink) GFDL-ESM2M (b) (orange) MPI-ESM-LR1 (c) (green) CanESM2 (d) (blue) CESM1-LE. The average coefficient of variance variation of the synthetic ensemble (SE) created using the MODIS surface ocean chlorophyll record is shown in the purple dot on the vertical axis (Elsworth et al., 2020, 2021). Trend significance is determined by a t-test with a p-value less than 0.05.

- To provide context for the CESM1-LE results, we examine changes in chlorophyll variance internal variability from a subset of the Coupled Model Intercomparison Project 5 (CMIP5) models (Taylor et al., 2011): the GFDL-ESM2M from the Geophysical Fluid Dynamics Laboratory (GFDL; (Dunne et al., 2012, 2013), the CanESM2 from the Canadian Centre for Climate Modelling and Analysis (Christian et al., 2010; Arora et al., 2011), and the MPI-ESM-LR from the Max Planck Institute (MPI; (Giorgetta et al., 2013; Ilyina et al., 2013), consisting of 30, 50, and 100 ensemble members, respectively. Similarly to the CESM1-LE, historical forcing was applied through 2005, followed by RCP8.5 forcing through 2100.
- We compare the variance internal variability in chlorophyll observed among the large ensembles to a synthetic ensemble generated from observational chlorophyll concentrations over the MODIS remote sensing record (Elsworth et al., 2020, 2021). A synthetic ensemble is a novel technique that allows the observational record to be statistically emulated to create multiple possible evolutions of the observed record, each with a unique sampling of internal climate variability (McKinnon et al., 2017; McKinnon and Deser, 2018). We use the synthetic ensemble of chlorophyll concentration to compare the variability observed
- 660 in the real world to the variability simulated across a suite of ESM ensembles.

 Table S2. Summary statistics for the t-test performed on total phytoplankton biomass to determine trend significance across the RCP8.5

 forcing scenario (2006 to 2100). Datasets are normally distributed.

Variable	Sample Size	Mean	Standard Error	<u>95% CI</u>
Total Phytoplankton Biomass Mean Trend	<u>94</u>	-0.0697	0.00459	-0.0743 to -0.0651
Total Phytoplankton Biomass Standard Deviation Trend	<u>94</u>	-0.0164	0.00323	-0.0196 to -0.0132

**Figure S4.** (a) Total phytoplankton carbon concentration simulated by the CESM1-LE in mmol C m<sup>-2</sup> averaged across the RCP8.5 forcing scenario (2006 to 2100). (b) Internal standard deviation in total phytoplankton carbon concentration averaged over the same period. The change in the coefficient of variation is calculated using averages across the first (2006 to 2016) and last (2090 to 2100) decades of the RCP8.5 forcing scenario.

To provide context for Figure 3, we include the spatial distribution of total phytoplankton carbon concentration (Figure \$3\$54a) and internal standard deviation in phytoplankton carbon concentration (Figure \$3\$54b) simulated by the CESM1-LE across the RCP8.5 forcing scenario (2006 to 2100). Total phytoplankton carbon concentration is relatively high in the subpolar Atlantic and Pacific, the Southern Ocean, and the Eastern Equatorial Upwelling Zone and relatively low in the subtropical gyre regions (Figure \$3\$4a). Regions of relatively high phytoplankton carbon concentrations correspond to regions of high variance

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internal variability (Figure S3S4b).

(a) Total phytoplankton carbon concentration simulated by the CESM1-LE in mmol C m<sup>-2</sup> averaged across the RCP8.5 forcing scenario (2006 to 2100). (b) Internal standard deviation in total phytoplankton carbon concentration averaged over the same period.

670 Reconstructed changes in the contribution of each driver variable to phytoplankton biomass variance across the RCP8.5 forcing scenario (2006 to 2100) using variable regression coefficients between the beginning and end of the century. Regions were selected which aligned with the highest fisheries catch in the (a) Atlantic and (b) Pacific basins with the beginning of the century shown in light blue and the end of the century shown in dark blue.

Reconstructed global changes in the contribution of each driver variable to changes in (a) mean phytoplankton biomass and
 (b) phytoplankton biomass variance across the RCP8.5 forcing scenario (2006 to 2100). The beginning of the century is shown in light blue and the end of the century is shown in dark blue.

Reconstructed global changes in the contribution of each driver variable to changes in (a) mean phytoplankton biomass and (b) phytoplankton biomass variance across the RCP8.5 forcing scenario (2006 to 2100) across the beginning of the century. The contribution of cross terms to the MLR reconstruction is shown in the rightmost bar in each panel.

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Reconstructed changes in the contribution of each driver variable to mean phytoplankton biomass across the RCP8.5 forcing scenario (2006 to 2100) with the beginning of the century shown in light blue and the end of the century shown in dark blue. Marine ecological regions are defined in Tagliabue et al. (2021). Regions were selected which aligned with the highest fisheries eatch in the (a) Atlantic and (b) Pacific basins and the biogeochemically important (c) Southern Ocean and (d) Equatorial

Pacific regions. The dominant phytoplankton functional type is considered in each region. In regions with a mixed ecological

685 assemblage, total phytoplankton carbon is considered.

Reconstructed changes in the contribution of sea surface temperature and diatom carbon to changes in diatom grazing variance in the Atlantic supolar (ASP) region across the RCP8.5 forcing scenario (2006 to 2100). The contribution of the change in diatom biomass variance dominates the change in diatom grazing variance.