

1 Controls of cross-shore planktonic ecosystem structure 2 in Eastern Boundary Upwelling Systems

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6 **Key Points:**

- 7 • An idealized quasi-2D model (MAMEBUS) of Eastern Boundary Upwelling Sys-
8 tems (EBUSs) and coupled size structured ecosystem model is presented
- 9 • Controls on the across-shore phytoplankton size structure are identified by a set
10 of model experiments
- 11 • Idealized simulations configured to the California Current System (CCS) show wind
12 stress maximum and nutrient concentration in upwelled water set zonal plankton
13 size distributions

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14 **Abstract**

15 Eastern boundary upwelling systems (EBUSs) are among the most productive regions
 16 in the ocean because deep, nutrient-rich waters are brought up to the surface. Previous
 17 studies have identified winds, mesoscale eddies and offshore nutrient distributions as key
 18 influences on the net primary production in EBUSs. However uncertainties remain re-
 19 garding their roles in setting cross-shore primary productivity and ecosystem diversity.
 20 Here, we use a quasi-two-dimensional (2D) model that combines ocean circulation with
 21 a spectrum of planktonic sizes to investigate the impact of winds, eddies, and offshore
 22 nutrient distributions in shaping EBUS ecosystems. A key finding is that variations in
 23 the strength of the wind stress and the nutrient concentration in the upwelled waters con-
 24 trol the distribution and characteristics of the planktonic ecosystem. Specifically, a strength-
 25 ening of the wind stress maximum, driving upwelling, increases the average planktonic
 26 size in the coastal upwelling zone, whereas the planktonic ecosystem is relatively insen-
 27 sitive to variations in the wind stress curl. Likewise, a deepening nutricline shifts the lo-
 28 cation of phytoplankton blooms shore-ward, shoals the deep chlorophyll maximum off-
 29 shore, and supports larger phytoplankton across the entire domain. Additionally, increased
 30 eddy stirring of nutrients suppresses coastal primary productivity via “eddy quenching”,
 31 whereas increased eddy restratification has relatively little impact on the coastal nutri-
 32 ent supply. These findings identify the wind stress maximum, isopycnal eddy diffusion,
 33 and nutricline depth as particularly influential on the coastal ecosystem, suggesting that
 34 variations in these quantities could help explain the observed differences between EBUSs,
 35 and influence the responses of EBUS ecosystems to climate shifts.

36 **Plain Language Summary**

37 Ecosystems in Eastern Boundary Upwelling Systems (EBUSs) are supported by
 38 the movement of nutrient-rich water from the deep ocean to the coastal surface waters
 39 through a wind-driven process called “upwelling”. Many factors can impact the across-
 40 shore (zonal) distribution of size in EBUSs, with abundant large phytoplankton near shore,
 41 and sparse small phytoplankton offshore. For example, the strength of the wind controls
 42 upwelling, the subsurface nutrient distribution determines surface nutrient supply, and
 43 large-scale ocean vortices (“eddies”) remove nutrients from the surface. However, there
 44 remains uncertainty as to the relative importance of these different factors in determin-
 45 ing the sizes and abundance of phytoplankton upwelling ecosystems. This study utilizes
 46 a physical ocean model coupled to an ecosystem model to investigate the impact of var-
 47 ious physical and biological influences on planktonic ecosystems in EBUSs. We find that
 48 the strength of the wind, the mixing of nutrients by eddies, and the concentration of nu-
 49 trients in the upwelled waters are most important in determining the ecosystem struc-
 50 ture. In contrast, cross-shore variations in the wind and the tendency of eddies to push
 51 waters downward near the coast are less influential. Our findings provide clarity on how
 52 physical and biochemical aspects of the EBUS environment influence its ecosystem.

53 **1 Introduction**

54 Eastern Boundary Upwelling Systems (EBUSs) support productive and diverse bi-
 55 ological communities (Chavez & Messié, 2009; Bakun & Parrish, 1982). The along-shore
 56 equatorward winds drive an offshore transport of surface water and resulting upwelling
 57 of dense, nutrient-rich water to the surface (Bakun & Nelson, 1991; M. Jacox & Edwards,
 58 2012; M. J. Jacox & Edwards, 2011). At the same time, a complex interplay of physi-
 59 cal phenomena that arise as a consequence of upwelling often works to redistribute and
 60 even subduct nutrients in a process known as “eddy quenching”, which ultimately re-
 61 duces surface productivity (Colas et al., 2013; Gruber et al., 2011). Understanding re-
 62 sponses of the local food-web to these and other forms of variability in the physical en-

63 vironment is important for regional socioeconomic stability (Golden et al., 2016; Pozo Buil
64 et al., 2021).

65 Ecological responses to wind-driven upwelling in EBUSs have long been studied (Messié
66 et al., 2009; Van Oostende et al., 2018; Gruber et al., 2011; Renault et al., 2016), yet un-
67 certainties remain in the response of ecosystem diversity and the regional structure of
68 the food-web. While the location of phytoplankton blooms and biomass is predominantly
69 set by the total nutrient supply and availability (Marañón et al., 2014), the controls on
70 the zonal ecosystem composition in EBUSs are less clear. In regions of high productiv-
71 ity near the coast, large phytoplankton contribute to the plurality of the biomass (Shel-
72 don et al., 1972; Hood et al., 1991; Taylor et al., 2012), whereas offshore in the deep chloro-
73 phyll maximum, small phytoplankton dominate the total biomass (Worden et al., 2004;
74 Zubkov et al., 2000).

75 A variety of physical influences have been shown to be important in determining
76 the structure of the food-web in EBUSs. This structure varies as a consequence of zon-
77 ally variable nutrient variability, described as follows. The strength of the wind, which
78 drives upwelling, combined with the subsurface nutrient concentration controls the to-
79 tal productivity in EBUSs. In general, with stronger upwelling associated with higher
80 coastal surface productivity (Capet et al., 2004; Chavez & Messié, 2009; Rykaczewski
81 & Dunne, 2010; Pozo Buil et al., 2021). Within our parameter space, we expect an in-
82 crease in the overall strength of the wind to support higher phytoplankton biomass and
83 larger cell sizes (Hood et al., 1991). However, studies have show that there exists a trade-
84 off in upwelling strength in productivity, with very strong upwelling reducing surface pro-
85 ductivity Botsford et al. (2006).

86 While meridional equatorward winds drive bulk coastal upwelling and support pro-
87 ductivity, they also generate a baroclinically unstable jet that sheds mesoscale eddies that
88 restratify the water column, and transports nutrients and other tracers away from the
89 euphotic zone, reducing productivity (Gruber et al., 2011; Colas et al., 2013; Capet et
90 al., 2008).

91 Renault et al. (2016) found that the shape of the wind-stress curl controls the coastal
92 flux of nutrients and net primary productivity in the euphotic zone, with a wider wind-
93 stress curl associated with weaker “eddy quenching” and higher net primary production.
94 As a consequence, EBUSs are characterized by a zonal gradient of productivity that spans
95 several orders of magnitude between the coast and the oligotrophic open ocean. These
96 differences in nutrient concentrations drive changes in ecosystem composition (Hood et
97 al., 1991; Worden et al., 2004; Taylor et al., 2012). Eddy restratification, eddy stirring,
98 and subduction have been suggested to reduce the total productivity at the surface and
99 on the shelf (Renault et al., 2016; Colas et al., 2013). Thus, insofar as productivity and
100 phytoplankton size are positively related (Van Oostende et al., 2018; Moscoso et al., 2022),
101 an increase in eddy kinetic energy would work to decrease the size of plankton near the
102 coast (Renault et al., 2016).

103 The composition of upwelled source waters also impacts the ecosystem structure.
104 While physical controls can modulate the depth of the source water (M. J. Jacox & Ed-
105 wards, 2011), the subsurface concentration of nutrients in the subtropics also impacts
106 the nutrients that are upwelled (Pozo Buil et al., 2021). A shallow, sharp nutricline in-
107 creases the amount of nutrients on the shelf, provided that the source depth of upwelled
108 water does not change (M. Jacox & Edwards, 2012), and leads to an increase of produc-
109 tivity and plankton size near the coast.

110 Previous modeling work has been successful in capturing zonal patterns of phyto-
111 plankton productivity and size in regional frameworks. Goebel et al. (2010) shows a zonal
112 transition from large plankton onshore to small plankton offshore in the California Cur-
113 rent System (CCS) with an intermediate complexity biogeochemical model. Similarly,

114 Van Oostende et al. (2018) showed that a large diatom class was essential in capturing
 115 a near-shore surface chlorophyll maximum over an upwelling season in the Southern California
 116 Bight. Due to computational limitations of realistic, three-dimensional (3D) re-
 117 gional models, a systematic characterization of the responses of ecosystem diversity to
 118 biogeochemical and physical forcing in EBUSs is still lacking. Additionally, the factors
 119 that control the distribution of nutrients in EBUSs often co-vary. For example, eddies
 120 drive both restratification and advection along isopycnal surfaces, and are influenced by
 121 wind changes. These processes are hard to disentangle in complex, 3D eddy-resolving
 122 models. In contrast, the use of idealized models allows an independent exploration of the
 123 effects of individual model parameters, and can decouple the effects of physical processes
 124 that often co-vary in more complex regional models.

125 In this study, we conduct an expansive exploration of the ecological responses to
 126 upwelling under a wide parameter space. We configure an idealized quasi-2D Meridion-
 127 ally Averaged Model of Eastern Boundary Upwelling Systems (MAMEBUS, Moscoso et
 128 al. (2021); Stewart & Moscoso (2020)) to examine a large number of physical states rep-
 129 resentative of those found across the CCS. The physical model includes a finely-resolved
 130 size-structured ecosystem model (Moscoso et al., 2022; Banas, 2011; Ward et al., 2012)
 131 that represents the lower-trophic food-web cycling. Size-structured ecological models are
 132 often used to represent broad functional diversity in the food-web because size is gen-
 133 erally an excellent proxy for other biological traits (Andersen et al., 2016), and are be-
 134 coming common for global Earth system models (Ward et al., 2012; Henson et al., 2021;
 135 Negrete-García et al., 2022). In general, size-structured ecosystems with a fine resolu-
 136 tion of the size dimension have not been studied in comprehensive regional and global
 137 models due to computational constraints. However, using a quasi-2D model, we are able
 138 to explore the behavior of a highly resolved planktonic food-web structure in an ideal-
 139 ized framework.

140 The remainder of the paper is organized as follows: In Section 2, we describe the
 141 physical and biogeochemical model configurations, and discuss model parameters and
 142 their range. We additionally define model diagnostics used to identify the responses to
 143 perturbations in the model state. In Section 3, we present a reference solution focusing
 144 on ecosystem size structure and characteristics. In Section 4, we discuss the responses
 145 to variations across the parameter space in three sub-regions of an idealized EBUS to
 146 identify important controls. Finally, in Section 5, we discuss the results and their im-
 147 plications for ecosystem productivity and diversity in EBUSs.

148 2 Methods

149 The simulations presented in this study were conducted using a Meridionally Av-
 150 eraged Model of Eastern Boundary Upwelling Systems (MAMEBUS, Moscoso et al. (2021)),
 151 a quasi-2D idealized model coupled to a size-structured nutrient, phytoplankton, zoo-
 152 plankton, detritus (NPZD) model (Moscoso et al., 2022). A schematic of the main com-
 153 ponents of the model is shown in Figure 1. The physical setup of the model is similar
 154 to that presented in Moscoso et al. (2021); any differences in the model configuration are
 155 highlighted below.

156 2.1 Physical Model Configuration

157 We configure MAMEBUS to represent an idealized CCS in a quasi-2D framework.
 158 While 2D models have been used to investigate upwelling with respect to a wide phys-
 159 ical parameter space in other studies of productivity in EBUSs (M. J. Jacox & Edwards,
 160 2011; M. Jacox & Edwards, 2012), some of the 3D processes that have been shown to
 161 be important in controlling biological responses (Renault et al., 2016; Gruber et al., 2006)
 162 were not explicitly resolved. However, MAMEBUS includes a series of parameterizations
 163 that improve representation of these processes: The momentum equations are calculated

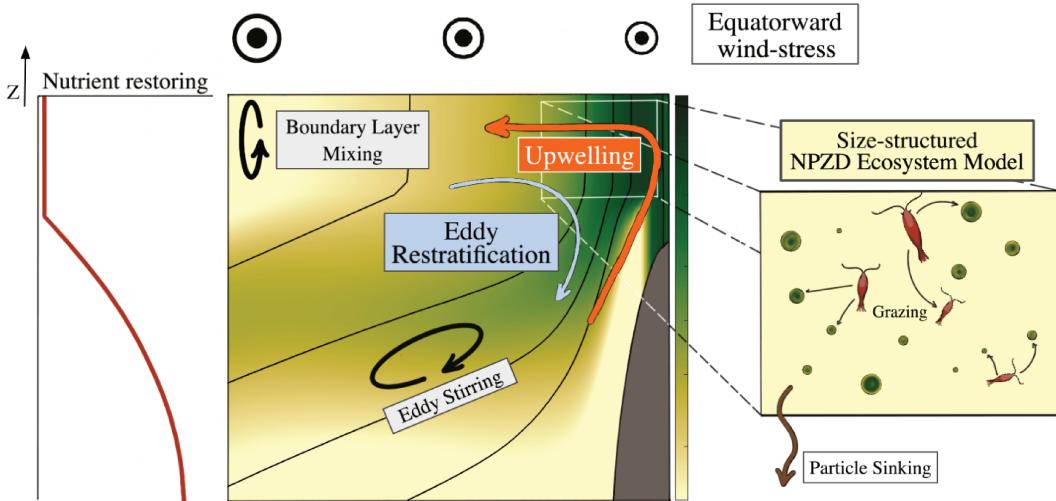


Figure 1: A schematic showing the major components of the coupled physical-biogeochemical model used in this study. Color contours in the central panel show total phytoplankton concentration, the black lines are isotherms, and the topography is shown in dark grey. The mean circulation is determined by wind-driven upwelling. Eddy restratification, eddy stirring, and boundary layer mixing are parameterized. Temperature and nutrients are restored to observed profiles at the western boundary, shown here in the left panel. The ecosystem component (right panel) consists of a size-structured ecosystem model with 50 phytoplankton and 50 zooplankton size classes.

following Dauhajre & McWilliams (2018). The effect of eddy restratification is parameterized following Gent & McWilliams (1990), eddy stirring along isopycnals is parameterized following Redi (1982) and surface and bottom boundary layer mixing is calculated following Ferrari et al. (2008). The detailed formulation of each of these parameterizations is described in Moscoso et al. (2021).

The physical design of MAMEBUS is meant to capture the broad behavior of upwelling in an idealized EBUS. Here, we configure the model to represent an idealization of the southern CCS. However this parameter space may encompass sections of parameter spaces found in other EBUSs. The model grid is cast in terrain-following coordinates. The model domain spans from the coast to 400 km offshore, and from the surface to 50m depth on the eastern (i.e., coastal) boundary of the domain, and 4000m depth on the western (i.e., open-ocean) boundary. At the eastern boundary, the shelf is prescribed to be deeper than what is found along the coast in order to reduce the model's computational time. The boundary conditions for temperature and nitrate at the western boundary are based on observations from The California Cooperative Oceanic Fisheries Investigations (CalCOFI) from Line 80 at Stations 90 and 100 from 1997 – 2018.

The topography is an idealized slope that follows ETOPO5 near Point Conception (Amante & Eakins, 2009), and slightly differs from that presented in Moscoso et al. (2021) by adopting a steeper slope to better represent the bathymetry near Point Conception, California (Line 80, CalCOFI). The model resolution is 60 horizontal grid-points and 60 vertical levels. This corresponds to an approximate grid-spacing of 6.7 km in the horizontal. MAMEBUS employs a stretched vertical coordinate, so the approximate vertical grid-spacing varies across the domain, from a minimum of 0.5 m near the coast to a maximum of ~ 215 m at the western boundary.

188 The wind stress forcing is designed to approximate the median of monthly climatic
 189ologies of data from ECMWF Reanalysis v5 (ERA5, Hersbach et al. (2020)) and from
 190 the Weather Research and Forecasting Model (WRF V4.1, Skamarock et al. (2008)) from
 191 1997 – 2017. The along-shore component of the wind stress is calculated as an along-
 192 shore average from 34.5°N to 35°N, and shown as a function of distance from the coast
 193 over a 400km offshore extent for comparison to *in situ* data from Line 80 in CalCOFI
 194 data. This line is chosen because it falls between the latitudes where the data used for
 195 model configuration and forcing are averaged.

Specifically, the wind stress profile used in the model is given by:

$$\tau(x) = \tau_{\max} \tanh\left(\frac{L_x - x}{L_x/\tau_x}\right), \quad (1)$$

196 where τ_{\max} (N/m²) is the wind stress maximum, L_x is the width of the model domain,
 197 and τ_x is a dimensionless tuning parameter that controls the width of the wind stress
 198 curl. Higher values of τ_x correspond to a narrower wind stress curl; however, the mag-
 199 nitude of the offshore wind stress does not change. The wind stress curl is given by $\partial_x \tau(x)$
 200 (N/m³). The reference wind stress profile is shown in Figure 2. In all instances of the
 201 model, described in Section 2.3, the wind-stress forcing is held constant. While there is
 202 substantial seasonality in the strength and shape of the wind across EBUSs Capet et al.
 203 (2004); Castelao & Luo (2018), we are interested in understanding the long-term steady-
 204 state behavior of the ecosystem, thus all physical forcing is constant.

To represent the offshore conditions that are set by processes occurring in the Pacific Ocean we define a 50km sponge layer on the western boundary of the domain. In this sponge layer, temperature and nitrate are restored to profiles that approximate *in situ* observations. The offshore temperature profile is defined as

$$T_R(z) = T_{\min} + (T_{\max} - T_{\min}) \cdot \left(\frac{\exp\left(\frac{z}{\Delta T_Z} + 1\right) - \exp\left(\frac{-H}{\Delta T_Z} + 1\right)}{\exp(1) - \exp\left(\frac{-H}{\Delta T_Z} + 1\right)} \right), \quad (2)$$

205 where T_{\min} is the minimum temperature in the water column, T_{\max} is the maximum tem-
 206 perature, ΔT_Z is the temperature decay scale, and $-H$ is the maximum depth of the wa-
 207 ter column. A reference buoyancy restoring profile is shown in Figure 3. At the surface,
 208 temperature is also restored to an idealized gradient based on observations from CalCOFI
 209 (see Moscoso et al. (2021)). The eastern boundary and the ocean floor have no flux bound-
 210 ary conditions.

211 2.2 Biogeochemical Model Configuration

212 MAMEBUS (Moscoso et al., 2021) is coupled online to a size structured NPZD model
 213 (SSEM, Moscoso et al. (2022)) based on previous work by Banas (2011) and Ward et al.
 214 (2012). Size is used as a proxy for ecological diversity, reflecting strong relationships be-
 215 tween organism size and resource encounter strategies. This choice reduces the dimen-
 216 sionality of the model parameter space (compared to models which simulate multiple func-
 217 tional groups), while capturing important ecological behaviors (Follows & Dutkiewicz,
 218 2011; Sauteray et al., 2017; Loeuille & Loreau, 2005; Banas, 2011). The size-dependent
 219 processes represented by the model include nutrient uptake by phytoplankton, heterotrophic
 220 grazing by zooplankton, predator-prey size interactions, plankton mortality, and size dif-
 221 fusion (i.e., mutation). Large phytoplankton have slow uptake rates, tend to be more nu-
 222 trient limited, and have longer lifespans than their smaller counterparts (Tang, 1995; Ep-
 223 pley et al., 1969). The grazing dynamics are modeled under the assumption that small
 224 zooplankton quickly graze phytoplankton of approximately the same size, while large zoo-
 225 plankton prefer proportionally smaller prey, and have slower grazing rates (Hansen et
 226 al., 1994). However, this is an approximation that may not be representative of all zoo-
 227 plankton (Kiørboe, 2011). We parameterize phytoplankton mutations as a weak diffu-

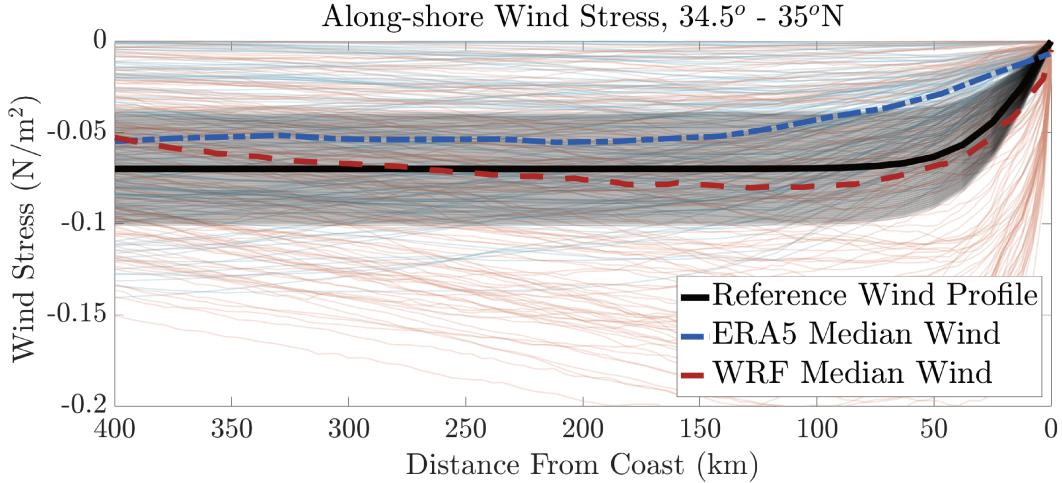


Figure 2: Wind profiles derived from ECMWF Reanalysis v5 (ERA5), and Weather Research & Forecasting Model (WRF), in blue and red, respectively. The thick lines show the median wind profiles for each reanalysis product, and the black line shows the reference wind profile used in MAMEBUS, with the black shaded area indicating the range of profiles used in the sensitivity analysis. The thin lines correspond to monthly averaged wind profiles from 1997-2017.

228 sion in size space, which allows for plankton to grow or shrink over relatively long timescales
 229 (Sauterey et al., 2017).

230 When size structured ecosystem models are highly resolved in trait-space and use
 231 size-dependent grazing interactions, the biomass aggregates along preferential modes, or
 232 peaks, along the size spectrum – a behavior that we refer to as size “quantization” (Ba-
 233 nás, 2011; Moscoso et al., 2022). In zero dimensions, Moscoso et al. (2022) found that
 234 the location of these biomass peaks is approximately explained by a measure of selec-
 235 tivity in zooplankton grazing, namely, the width of the grazing profile, $\Delta\ell$. This vari-
 236 able controls the grazing behaviour of zooplankton with small values of $\Delta\ell$ limiting the
 237 number of size classes zooplankton can graze, and larger values allowing for less selec-
 238 tive grazing. As such, small values of $\Delta\ell$ correspond to an ecosystem with highly spe-
 239 cialized zooplankton grazers. In this configuration, there are more biomass peaks along
 240 the size spectrum with more plankton diversity in size space (Vallina et al., 2014). In
 241 the limit of $\Delta\ell \rightarrow 0$, there is no quantization in biomass (Poulin & Franks, 2010). While
 242 the formulation of the grazing controls the biomass peaks, the nutrient availability al-
 243 lows for the emergence of large size classes with the approximate spacing between peaks
 244 determined by the value of $\Delta\ell$. Quantization establishes on the timescale of approximately
 245 one year under both constant (Moscoso et al., 2022) and variable nutrient forcing (Ba-
 246 nás, 2011).

247 The configuration of the model is similar to that presented in Moscoso et al. (2022),
 248 with the following changes: In this study, we set $\Delta\ell = 0.2$ as our representative graz-
 249 ing profile width (Hansen et al., 1994). Based on prior simulations, we use 50 phytoplank-
 250 ton and zooplankton size classes, as this is the minimal number of classes to resolve quan-
 251 tization in biomass and converge to a steady state equilibrium over time. The 50 phy-
 252 toplankton size classes are log-linearly spaced between $0.2 \mu\text{m}$ and $100 \mu\text{m}$, and the 50 zooplankton
 253 size classes are log-linearly spaced between $0.5 \mu\text{m}$ and $5000 \mu\text{m}$. All phytoplankton classes are initialized to a constant value of $0.1 \text{ mmol N m}^{-3}$, and all zooplankton are initialized to $0.01 \text{ mmol N m}^{-3}$.

256 We simulate a single nutrient pool that represents nitrate, since nitrogen is the main
 257 limiting nutrient in the California Current (Deutsch et al., 2021), and nitrate fluxes are
 258 often used in EBUSs as proxies of productivity (Chavez & Messié, 2009; Messié et al.,
 259 2009; M. Jacox & Edwards, 2012). Note that the model formulation does not explicitly
 260 include a distinction between new and regenerated production (Karl, 2002). However,
 261 in regions of high productivity, new production often dominates over regenerated pro-
 262 duction (Sarmiento & Gruber, 2006; Messié et al., 2009). The nitrate profile is initial-
 263 ized to the restoring profile everywhere in the domain, but only restored in the sponge
 264 layer after initialization, as described by Equation 3.

265 The model includes a single particulate detritus pool, with a constant sinking speed
 266 of 10 m d^{-1} . Thus, we do not include size-dependent sinking or size structure in the de-
 267 tritus component, recognizing that this choice may be important in determining verti-
 268 cal nutrient fluxes to the deep ocean (Kriest, 2002; Polimene et al., 2017). Detritus is
 269 initialized to zero everywhere in the domain and at the lower boundary detritus has a
 270 no flux condition, and is remineralized to nitrate in the lowest grid-cell.

At the western boundary, nitrate is restored to an idealized profile defined as,

$$N_R(z) = \begin{cases} 0 & z \leq \zeta_N^0 \\ N_{\min} - N_{\max} \tanh\left(\frac{z + \zeta_N^0}{\Delta\zeta_N}\right) & z > \zeta_N^0 \end{cases} \quad (3)$$

271 where N_{\min} is the minimum surface nutrient concentration, N_{\max} is the maximum sub-
 272 surface nutrient concentration, ζ_N^0 is the nutrient restoring depth, and $\Delta\zeta_N$ is the nu-
 273 trient decay scale. This functional representation is based on an idealized fit to obser-
 274 vations, shown in Figure 3, with parameters tuned to approximately track the median
 275 profile of all observations. Note that both the thermocline and nutricline do not always
 276 align in the data (not shown) and are characterized by variable vertical scales. Thus, the
 277 profiles of these two variables are varied independently in the parameter sweeps presented
 278 in Section 2.3.

279 2.3 Sensitivity Experiments

280 The parameter range for the wind profile and nutrient restoring profile are chosen
 281 from data and reanalysis products, with perturbations that represents natural variabil-
 282 ity in the data. The ranges of the eddy diffusivities are informed by previous work by
 283 Colas et al. (2013), Abernathey & Marshall (2013) and Swenson & Niiler (1996). For each
 284 of parameter configuration, the model is spun-up with physics only for 30 model years
 285 with constant wind forcing, and buoyancy restoring at the surface and in the western
 286 sponge layer. For computational efficiency, the biogeochemical component of the model
 287 is activated during the last 10 model years (corresponding to a total of 40 years of phys-
 288 ical integration, and 10 years of coupled model integration). During the biogeochemi-
 289 cal spin-up, the size-structured ecosystem model exhibits some internal variability in the
 290 location of the biomass peaks. However, the peaks are well established after 1 model year,
 291 and sharpen over the remainder of the model run in both 0D and 1D configurations (Moscoso
 292 et al., 2022). The biological model is considered spun-up when the L2 norm of the dif-
 293 ference in biomass for every size class between time-steps is small ($O(10^{-3}) \text{ mmol N m}^{-3}$),
 294 for the reference state. This occurs after approximately five years, but the model is run
 295 for twice that length for analysis. All data reported and visualized in this study is av-
 296 eraged over the final model year. The range spanned by each parameter is shown in Ta-
 297 ble 1.

298 2.3.1 Wind Stress Forcing, τ_{\max} and τ_x

299 The two parameter sweeps that we choose to control the wind-profile are τ_{\max} , the
 300 maximum offshore wind stress, and τ_x , a tuning parameter that allows us to control the
 301 width of the wind stress curl. The ranges of values for τ_{\max} and τ_x are shown in Table

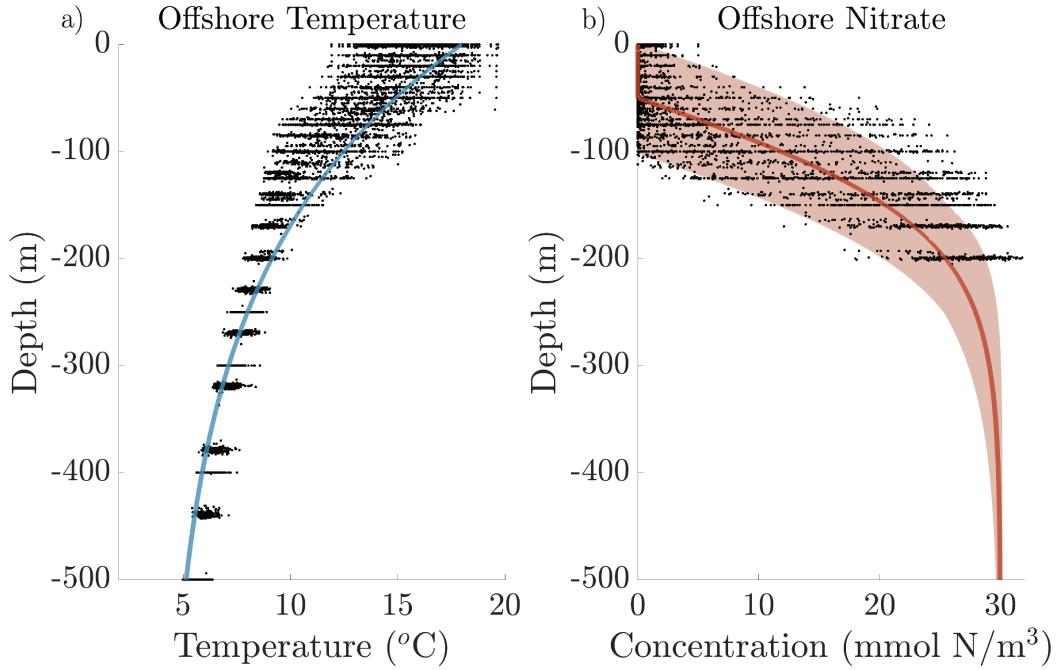


Figure 3: Restoring profiles for the temperature (left) and the nitrate (right). The black dots show data taken along Line 80 at stations 90 and 100 from California Cooperative Oceanic Fisheries Investigations (CalCOFI). Each point represents a nitrate measurement taken during cruises conducted in January, April, July, and October between 1997 and 2018. The shaded area (b) indicates the range of profiles used in the sensitivity analysis.

Table 1: Parameters varied in this study.

Parameter	Reference Value	Perturbation Range	Data or Reference	Description
τ_{\max}	0.05 N/m^2	$[0.01, 0.1] \text{ N/m}^2$	ERA5 and WRF Castelao & Luo (2018)	Offshore wind stress maximum
τ_x	12	[4, 18]	ERA5 and WRF Albert et al. (2010)	Width of wind stress curl
ζ_N^0	50 m	[0, 100] m	CalCOFI	Nutrient restoring depth
$\Delta\zeta_N$	120 m	[80, 160] m	CalCOFI	Nutrient decay scale
κ_{GM}	$1200 \text{ m}^2/\text{s}$	$[600, 1600] \text{ m}^2/\text{s}$	Swenson & Niiler (1996)	Maximum surface buoyancy diffusivity
κ_{iso}	$2400 \text{ m}^2/\text{s}$	$[1600, 2400] \text{ m}^2/\text{s}$	Abernathey & Marshall (2013)	Maximum surface isopycnal diffusivity

1, and are chosen to span the range of data from ERA5 and WRF. M. Jacox & Edwards (2012) find that a nearshore reduction in wind stress reduces inner shelf circulation and bottom boundary layer transport in the region of the wind stress curl. As a result, wind stress profiles with substantial nearshore curl show stronger upwelling and nutrient injection into the surface layer, while wind stress profiles with weaker near-shore curl show reduced surface nutrient concentrations (Albert et al., 2010).

2.3.2 Eddies, κ_{GM} and κ_{iso}

There are two components to the eddy parameterization in MAMEBUS that may have distinct impacts on ecosystem diversity: eddy advection (Gent & McWilliams, 1990),

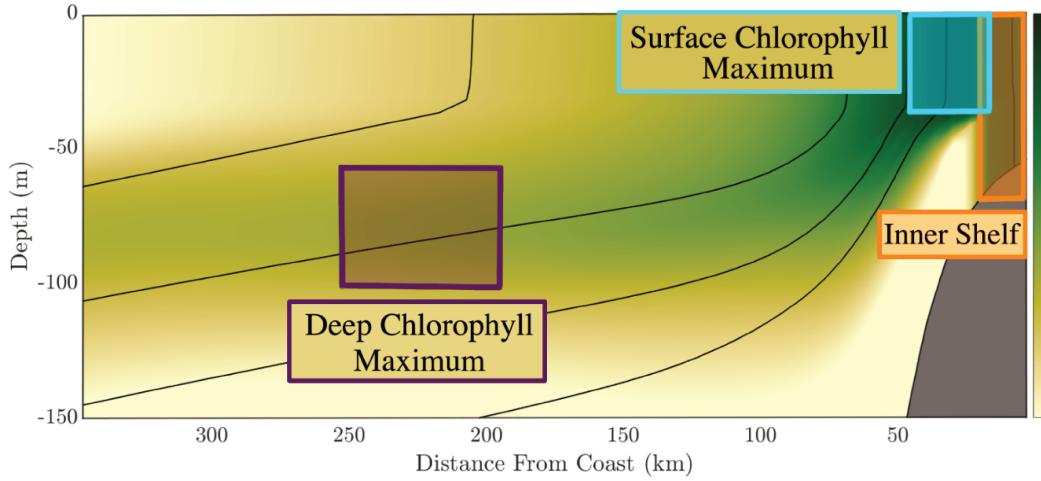


Figure 4: A schematic of the locations where ecosystem metrics are calculated. Metrics defined on the inner shelf are area averaged over the region where the surface and bottom mixed layers overlap. The surface chlorophyll maximum is defined as 25 km around the horizontal center of phytoplankton mass averaged over the mixed layer. The deep chlorophyll maximum is defined as the vertical center of mass of the total phytoplankton concentration averaged over 200–250 km from the coast, and 50 meters vertically. Color shading shows an example of phytoplankton distribution in the model, with temperature contours.

311 and isopycnal mixing (Redi, 1982). In these two parameter sweeps, we vary the strengths
 312 of the buoyancy diffusivity κ_{GM} , and the isopycnal diffusivity κ_{iso} . Reference profiles of
 313 the buoyancy and isopycnal diffusivity are shown in Moscoso et al. (2021) with surface
 314 intensified mixing (Lacasce, 2017). Additionally the reference values and the param-
 315 eter variations of κ_{GM} and κ_{iso} are given in Table 1.

316 **2.3.3 Offshore nutrient profile (boundary conditions), ζ_N^0 and $\Delta\zeta_N$**

317 In MAMEBUS, two parameters control the nutrients profiles in the open ocean.
 318 The first is the nutrient restoring depth, ζ_N^0 . This parameter allows us to set the level
 319 of oligotrophy in the surface ocean. Figure 3 shows the variations of the nutrient pro-
 320 file between 1997 – 2018 from Line 80 in CalCOFI. The nutrient restoring depth ζ_N^0 , varies
 321 from zero nutrients at the surface, to zero nutrients up to 100m depth. The second is
 322 the nutrient decay scale with depth, $\Delta\zeta_N$, which we vary to span the variability found
 323 in measured nutrient concentrations. The reference values and parameter variations of
 324 ζ_N^0 and $\Delta\zeta_N$ are given in Table 1.

325 **2.4 Model Diagnostics**

326 In this section, we define sub-regions in the model domain that are important to
 327 productivity in EBUSs and model diagnostics that will be calculated in each of these re-
 328 gions. The sub-regions we identify are the shelf, the surface chlorophyll maximum (SCM),
 329 and the deep chlorophyll maximum (DCM).

330 **2.4.1 Inner Shelf**

331 The inner shelf area is defined as the region on the shelf where the surface and bot-
 332 tom mixed layers overlap, shown in orange on Figure 4. This region is chosen because

Table 2: Table showing the area averaged model diagnostics calculated in the surface chlorophyll maximum, on the shelf, and in the deep chlorophyll maximum.

Diagnostic	Description
X_{\max}^{surf}	Surface Chlorophyll Maximum location
ζ_{DCM}	Deep Chlorophyll Maximum location
P_{tot}	Total phytoplankton concentration
Z_{tot}	Total zooplankton concentration
T	Temperature
U	Total uptake of nutrients by phytoplankton
ℓ_p^*	Concentration-weighted average size
H	Shannon index

upwelling is confined to the bottom boundary layer which directly links the surface to the subsurface. In all of our model simulations, the mixed layers overlap at approximately 25km from the coast. In this study, we do not vary the depth of the mixed layers, however, changes in mixed layer depths may be important in determining the nearshore concentration of plankton. The location of the inner shelf in the reference solution is shown in the orange box in Figure 4. Generally, the inner shelf is considered to be the shoaling region that connects the surf-zone to the continental shelf (Lentz & Fewings, 2012). However, we do not resolve a myriad of dynamics that are indicative of the inner shelf, including tides, buoyant plumes, and waves. For simplicity, we refer to the inner shelf region in this paper as the “shelf”.

2.4.2 Surface Chlorophyll Maximum (SCM)

We identify the surface chlorophyll maximum (SCM). Often in the CCS, we observe a coastal surface maximum in chlorophyll nearshore. However, this region may not occur over the shelf and can extend over the slope, as described in Section 2.4.1 because it may be closely tied to the ventilation of subsurface nutrients. We define the location of the SCM as a concentration-weighted distance from the coast, averaged vertically over the surface mixed layer, ζ_{sml} . Mathematically, we define the SCM as,

$$X_{\max}^{\text{surf}} = \frac{1}{P_{\text{tot}}^A} \overline{\int (P_{\text{tot}} \cdot x) \, dx}^{\zeta_{\text{sml}}}, \quad (4)$$

where P_{tot}^A is the total phytoplankton concentration in the integrated area, and P_{tot} is the total plankton concentration in the center of each model grid-box. An example of the location of the surface chlorophyll max is shown in the blue box in Figure 4.

2.4.3 Deep chlorophyll maximum (DCM)

DCMs are a common feature in EBUSs. The depth of the DCM is dependent on the balance between light available in the water column and nutrients available below, in regions where nutrients are not entrained into the surface mixed layer (Cullen, 1982; Zubkov et al., 2000; Tréguer et al., 2018). Brandini et al. (2014) proposed that a component of the horizontal advection could bring nutrients and productivity into the DCM from regions of strong Ekman forcing, but the magnitude of this contribution is not well constrained.

The DCM is defined as the off-slope region of the domain beneath the surface mixed layer, ζ_{sml} and above $\zeta_e = 200$ m depth, to encompass the depth of the euphotic zone.

This location of the DCM in the model domain is calculated halfway between the Eastern and Western boundaries of the domain. This choice was made to include the theoretical maximum depth of the euphotic zone, ~ -115 m in the absence of plankton and detrius, given our formulation of the irradiance profile in the biogeochemical model. The depth of the DCM is calculated as a biomass-weighted average depth,

$$\zeta_{\text{DCM}} = \frac{1}{P_{\text{tot}}} \overline{\int_{\zeta_e}^{\zeta_{\text{sml}}} (P \cdot z) \, dz}^x. \quad (5)$$

355 2.4.4 Ecosystem metrics

We introduce a series of metrics to quantify how ecological diversity responds to a set of physical forcings. The first is the concentration-weighted average size, defined as

$$\ell_p^* = \frac{1}{P_{\text{tot}}} \sum_i^{n_p} P_i \ell_{p_i}, \quad (6)$$

356 where P_i is the concentration of phytoplankton in the i -th size class, $P_{\text{tot}} = \sum_i P_i$, is
 357 the total phytoplankton concentration, $\ell_{p_i} \log_{10}(\mu\text{m})$ is the size of the phytoplankton in
 358 the i -th size class in log-space, and n_p is the number of phytoplankton size classes. If ℓ_p^*
 359 is large the center of planktonic mass in a specific model region is shifted toward larger
 360 phytoplankton size classes. Similarly, smaller average size indicates that the biomass is
 361 concentrated in smaller planktonic size classes.

To characterize the diversity of the planktonic ecosystem, following Spellerberg & Fedor (2003), we define the Shannon Index, H as,

$$H = - \sum_{i=1}^{n_p} \frac{P_i}{P_{\text{tot}}} \ln \left(\frac{P_i}{P_{\text{tot}}} \right). \quad (7)$$

362 We use the Shannon index to quantify the size diversity in various model regions. For-
 363 mally, the Shannon index is a measure of evenness in ecology, with lower values indicat-
 364 ing that biomass is more evenly distributed across all size classes. Together, the aver-
 365 age size and the Shannon Index allow us to identify, for example, regions of the model
 366 domain with the bulk of the phytoplankton biomass concentrated in the largest size classes
 367 (i.e. large ℓ_p^* and H).

368 We also include area-averaged diagnostics of total phytoplankton concentration,
 369 \overline{P} , total zooplankton concentration \overline{Z} , temperature \overline{T} , and the total uptake of nutrients
 370 by phytoplankton \overline{U} , a measure of net primary production. Here, the overbars denote
 371 area averages over the different diagnostic regions. The representation of uptake is de-
 372 scribed in Moscoso et al. (2022).

373 3 Simulated state and ecosystem properties

374 The model reproduces general patterns of productivity characteristic of EBUSs and
 375 the CCS including high productivity nearshore, a transition zone offshore, and a sub-
 376 surface DCM (Figure 5). At the surface, the model captures the zonal pattern of high
 377 biomass at the surface near the coast, and low biomass offshore. Similar patterns exist
 378 in zooplankton concentration. The DCM occurs at approximately 67m deep between 200-
 379 250 km from the coast.

380 The plankton biomass is concentrated around several specific locations along the
 381 size spectrum, exhibiting quantized behavior. Moscoso et al. (2022) conclude that biomass
 382 quantization is controlled by grazing, with the emergence of large size classes at increas-
 383 ingly high nutrient supply (Armstrong, 1994) and a gap between biomass peaks match-
 384 ing well theoretical estimates. Near the coast, where the total biomass is the highest, the

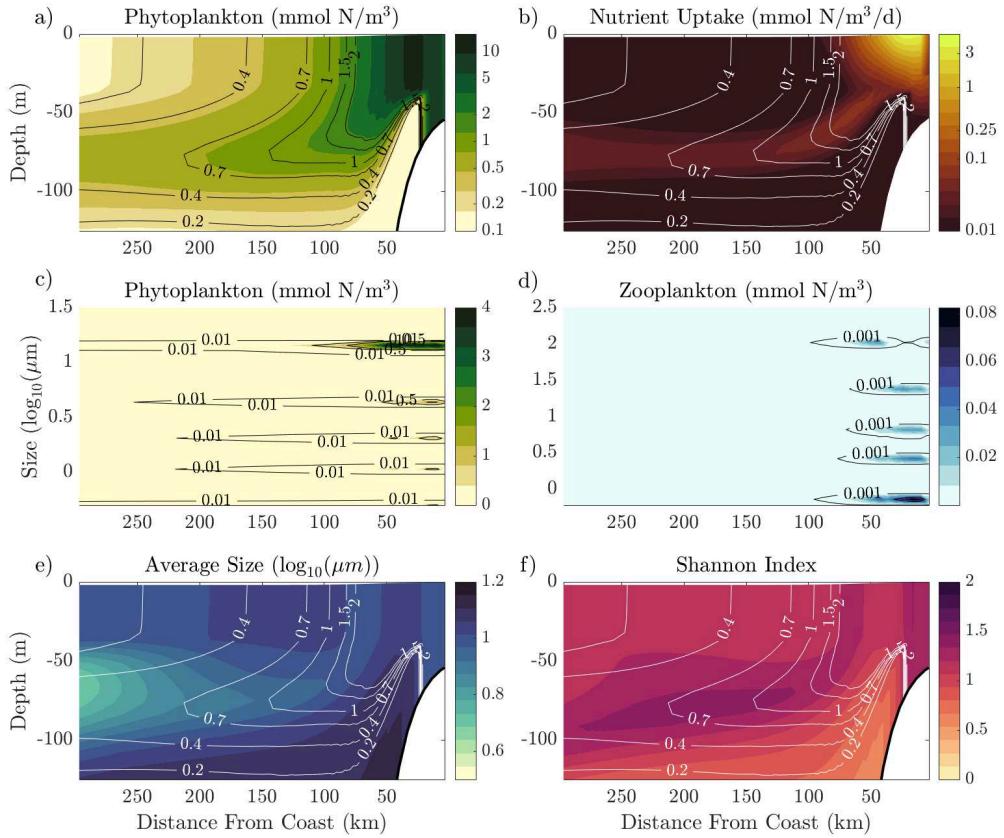


Figure 5: Size structure in our reference simulation over the model domain, outside of the restoring sponge layer at the western boundary. The top row of panels show the (a) total biomass of phytoplankton, and (b) the nutrient uptake per day. In (a) and (b), the total concentration of phytoplankton is shown in black and white contours, respectively. The middle panels show the biomass of (c) phytoplankton, and (d) zooplankton, averaged in the surface mixed layer as a function of distance from the coast and plankton size. The black lines in (c) and (d) are the biomass contours. The bottom panels show ecosystem metrics that consist of (e) concentration-weighted average size, and (f) Shannon Index. In (e) and (f), the total concentration of phytoplankton is shown in white contours.

385 largest phytoplankton size class contributes most to the total biomass. Offshore, the large
 386 size class still persists; however the intermediate size classes are not present above a con-
 387 centration of $0.01 \text{ mmol N m}^{-3}$. At depth across the entire domain, the average size of
 388 phytoplankton skews high, but the total biomass remains small. In this region, the largest
 389 size class does persist at very low concentrations. This regular spacing breaks down at
 390 approximately 170 km from the coast, where the width between peaks begins to increase.
 391 Here, the largest and smallest phytoplankton size classes persist. We assume that mor-
 392 tality is linearly proportional to phytoplankton uptake (n.b. Banas (2011)), therefore at
 393 small nutrient concentration, and thus slow nutrient uptake at large phytoplankton size
 394 classes, larger phytoplankton mortality is reduced. In regions, such as the surface mixed
 395 layer, with strong Ekman transport, large phytoplankton size classes may persist offshore.

396 Qualitatively, we find that large phytoplankton contribute to most of the biomass
 397 on the shelf. This is supported by a variety of observations, e.g., Hood et al. (1991) who
 398 found that large phytoplankton dominate at the surface in the shoreward side of an up-
 399 welling front. Offshore, in regions with lower total concentration, smaller phytoplank-

ton persist across more of the domain than the middle size classes. Figure 5 shows that the intermediate size classes are present in the nearest 200–250 km from the coast above 0.01 mmol m^{−3}. Previous work (e.g., Worden et al. (2004) and Taylor et al. (2012)) also shows that small phytoplankton dominate in the subtropical gyre and away from the nutrient-rich regions of the upwelling front.

Similar to phytoplankton, zooplankton also exhibit quantization. However, most of the biomass is concentrated in the smallest size classes in the surface waters within 100km from the coast. We suspect that this is a consequence of faster grazing rates for smaller zooplankton, faster mortality, and a wide grazing profile. In reality, we would expect the smaller zooplankton size classes to persist further offshore; however, here, zooplankton are mostly found on the shelf. Away from the coast, offshore of 100km, are very small concentration of zooplankton, < 0.001 mmol m^{−3}, which may explain the dominance of large phytoplankton offshore.

Figure 5 shows measures of the average size, ℓ_p , and the Shannon Index, H , for phytoplankton over the model domain in the mixed layer. Near the coast, in regions with high nutrient concentration and plankton biomass, the average size is the largest. Beneath the surface mixed layer, ($Z < -30$ m), the average size decreases, and in the DCM the smaller sizes dominate. For large values of H , the biomass is more equally distributed over many size classes, and for smaller values of H the biomass is aggregated among many size classes. In the SCM, the Shannon index slightly decreases, as the largest phytoplankton size class dominates in total biomass. Offshore and in the subsurface, the biomass is more evenly distributed, which is reflected in the Shannon Index. Between 50 and 100 m depth, approximately 300–350 km offshore, where the average size is at a local minimum, the Shannon index slightly decreases, implying that the smallest phytoplankton size classes dominate in this region. Below 125m depth, for total phytoplankton less than 0.2 mmol N m^{−3}, the largest size class persists, and dominates the total biomass.

A model-data comparison is additionally included in the Supplementary Information (see Figure S20 and associated text).

4 Ecosystem Sensitivity

In this section, we present the simulated responses of the model's physical state and ecosystem structure to variations in our control parameters (see Section 2). To quantify the model sensitivities, we normalize each diagnostic by its corresponding value from our reference simulation. In the same vein, the value of each control parameter, p , is normalized by the corresponding reference value, p_0 , in Table 1. This normalization allows us to compare relative changes with respect to reference values for all parameters and diagnostics simultaneously. With this normalization, we conduct linear fits for each of the parameter sweeps and use the slope of the best fit to identify the most important control parameters. Additionally, we calculate the percentage of variance about the best fit line, i.e., the R^2 , to determine how well a linear relationship explains the model behavior. Figure 6 shows the diagnostics (listed in Table 2) and the associated best fit line. The reference values for each of the control parameters in the diagnostic regions is listed in Table S1 in the Supplementary Information. Additionally, a full set of figures for each diagnostic is shown in the Supplementary Information .

While linear relationships are often useful in determining the first order behavior between our control parameters and model diagnostics, in some cases, a non-linear could be a more appropriate. To consider these cases, we calculate a secondary measure of of best fit with a second degree polynomial increases the measure of best fit. We list the leading coefficient, the R^2 value for the quadratic fit, and the difference between the measures of best fit for the polynomial and linear fits, see Figure S19 and Tables S2-S4. In general, an additional degree including an additional degree of freedom allows for a bet-

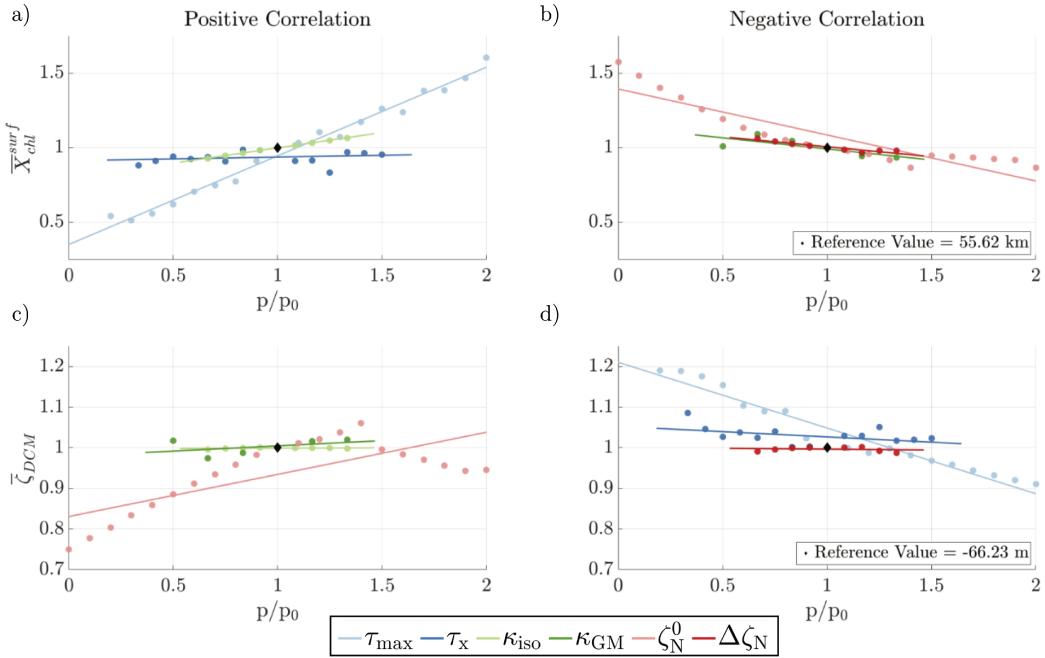


Figure 6: Responses of the location of the surface chlorophyll maximum (a,b) and the depth of the deep chlorophyll maximum (c,d). Model diagnostics are normalized relative to values from the control solution. Parameter sweeps with positive correlations are shown in the left column (a,c) and negative correlations in the right column (b,d). Parameters are normalized relative to the reference values (p_0) for comparison across parameter sweeps where τ_{max} is the maximum wind-stress, τ_x is the width of the wind-stress curl, κ_{iso} is the isopycnal mixing coefficient, κ_{GM} is the eddy advection coefficient, ζ_N^0 is the nutrient restoring depth, and $\Delta\zeta_N$ is the width of the nutricline.

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ter fit, therefore we select a threshold to indicate non-linear responses to the variables in our control parameters as $(R_{quad}^2 - R_{lin}^2) > 0.25$. In other words, 25% more of the variance is explained using the quadratic model.

We focus first on the sensitivity of the SCM and DCM positions, and then on the ecosystem response at these location to wind, eddies, and boundary conditions. We also identify significant correlations between various model diagnostics (Figure 8).

4.1 Regions of model diagnostics

In the reference case, the SCM is located approximately ~ 56 km from the eastern boundary of the model domain. The magnitude of the offshore wind-stress maximum is strongly correlated with the location of the SCM, with an increase in wind-stress increasing $\overline{X}_{chl}^{surf}$ (Figure 6 and 8). For brevity in this section, the values of the slopes and corresponding measures of best fit, R^2 , are given in the Supplementary Material. Dynamically, the strength of the wind determines the mean upwelling transport that carries nutrients to the surface (M. J. Jacox & Edwards, 2011; Capet et al., 2004; Bakun & Nelson, 1991), so this result agrees with previous findings. The location of the SCM is also sensitive to the nutrient restoring depth, ζ_N^0 . A shoaling of the nutrient restoring depth pushes the front offshore – i.e., it expands the productive coastal region. Likewise, a deepening moves the location of the SCM shore-ward, although with a weaker sensitivity. This response likely reflects total nutrient concentration in the source wa-

ters that are upwelled onto the shelf (M. J. Jacox & Edwards, 2011). In this case, we assume that the nutrient flux is a function of the upwelling flux and nutrient concentration, so the total upwelling and the nutrient concentration at upwelling depth are relevant.

The depth of the DCM, with a reference value of ~ -66 m, is less sensitive to changes in physical drivers. There is some dependence on the nutrient restoring depth, and the offshore wind-stress maximum. An increase in the magnitude of the wind-stress is associated with a shoaling of the DCM, and a strongly linear response ($R^2=0.94$). With increasing wind-stress, the strength of the upwelling increases, and more nutrients are brought to the surface (Capet et al., 2004; Messié et al., 2009). This shoals the nutricline in the model domain, driving the DCM toward the surface. Previous studies have proposed that the depth of the DCM is determined by a balance between the available light that penetrates from the surface and the nutrient availability at depth (Cullen, 1982; Zubkov et al., 2000; Tréguer et al., 2018). Nutrient profiles in turn are affected not only by lateral and vertical advection, but also by redistribution of organic matter by sinking particle fluxes, and subsequent remineralization. In this perturbation experiment, the depth of the DCM deepens with the nutrient restoring depth, although with very deep restoring depth, this relationship exhibits some nonlinearity. Light penetration from the surface is an important control on the depth of the DCM, and at very deep restoring there may be a compensation between the nutrient distribution and light limitation. In fact, we see that the phytoplankton biomass substantially decreases as nutrient restoring depth deepens.

The depth of the DCM exhibits non-linearity in the response to perturbations in ζ_N^0 . There is a domed shape in overall response to the depth of the nutricline. Over our parameter sweep, the depth of the DCM reaches a maximum at $1.4p/p_0$, and shoals, due to a combination of light and nutrient limitation.

4.2 Wind

Nearly all model diagnostics show a positive sensitivity to the wind stress maximum. Stronger winds increase the concentrations in phytoplankton and zooplankton across the model domain. The uptake on the shelf shows the strongest sensitivity, although the total biomass does not change as dramatically. Diagnostics of ecosystem diversity, ℓ_p and H , show small positive slopes and small R^2 values, indicating weak, nonlinear sensitivities (Figures S3 and S4). At very strong wind stress, the average size decreases due to the emergence of a new size class as a consequence of increased nutrients at the surface and in the SCM (see Figures S7 and S13). Similar nonlinear behavior is further seen in the DCM (see Figure S16 and S19). This can further be confirmed by a negative correlation in the shelf temperature, which implies stronger upwelling near the coast (Capet et al., 2004).

The width of the wind-stress curl has a significant negative impact on the zooplankton biomass in the DCM, while showing a minimal effect on phytoplankton biomass. This impact on zooplankton may reflect a negative impact on phytoplankton uptake. Further, the average size in the DCM increases when the width of the wind-stress curl decreases (Figure S6, and S16). However, this pattern is nonlinear with a peak near in the middle of our parameter space. A possible explanation for this could be that at low wind-stress forcing, an increase to upwelling allows for more nutrients to be delivered to the DCM. At high levels of forcing, a possible explanation could be that an increase in eddy activity and further remove nutrients from the DCM limiting large phytoplankton growth. The response is nearly opposite on the shelf, where a sharper wind-stress curl increases uptake and zooplankton biomass, while uptake slightly decreases in the SCM. This may indicate some non-linearity in the solutions, for example, see Figure S1 and S19.

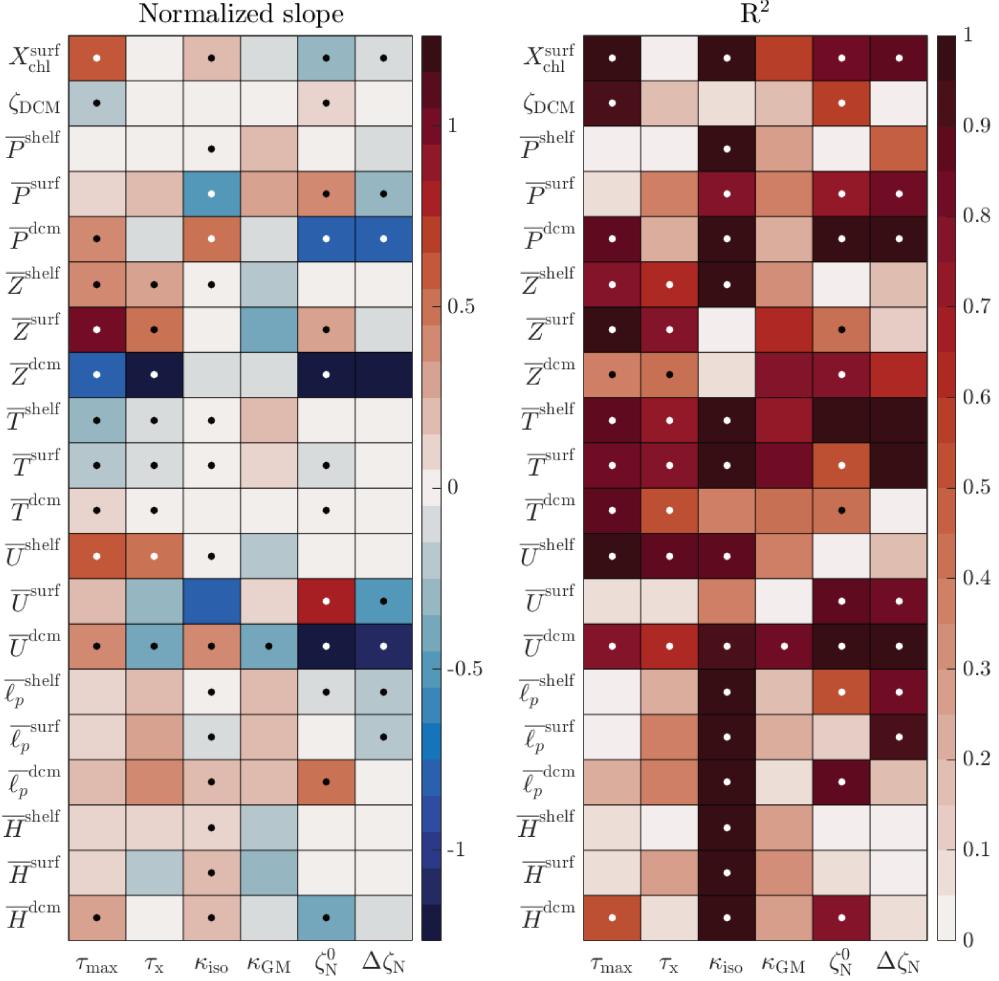


Figure 7: Correlation matrix showing the slope of the best fit line for each diagnostic (rows) along with the measure of best fit or R^2 value. The slope of the best fit line for each metric as a function of the control parameters (columns) is shown on the left. Each metric is area-averaged on the shelf, in the surface chlorophyll maximum, and in the deep chlorophyll maximum over one model year. The bullets in the center of the boxes indicate correlations that are statistically significant using the linear Pearson's correlation ($p < 0.01$).

519 Specific non-linear behavior can be seen in the average size of phytoplankton in all
 520 three diagnostic regions, in the phytoplankton biomass and the diversity index in the SCM
 521 and on the shelf, see Figure S19. Combined, this behavior indicates that there is an op-
 522 timal wind-stress which allows for a local maxima in the phytoplankton biomass and size,
 523 with a reduction in productivity at high wind-stress. This result follows work presented
 524 by Botsford et al. (2006) and García-Reyes et al. (2014).

525 4.3 Eddies

526 The isopycnal diffusivity, κ_{iso} shows statistically significant relationships with plank-
 527 ton biomass in all the diagnostic regions. The total phytoplankton biomass in the SCM
 528 and DCM show strong negative and positive slopes, respectively. This suggests that κ_{iso}
 529 transfers nutrients and phytoplankton from the SCM to the DCM. Our results are con-

530 sistent with previous work by Gruber et al. (2011), which showed that eddies tend to se-
 531 quester nutrients to depth and decrease surface productivity. While we find statistically
 532 significant relationships between the average phytoplankton size and the Shannon In-
 533 dex in the diagnostic regions, these relationships are weak (see Figures S9). In the SCM,
 534 higher isopycnal diffusion slightly decreases the average size of phytoplankton, while in-
 535 creasing the Shannon Index. Similar patterns are observed on the shelf (Figure S14). In
 536 both regions, the slight increase in diversity likely corresponds to a reduction of biomass
 537 in the larger size classes. Finally, in the DCM, both average size and diversity increase,
 538 likely as a result of increased nutrient supply by eddy stirring along isopycnals (Figure
 539 S17).

540 The effect of eddy restratification κ_{GM} is relatively small. On the shelf and in the
 541 SCM, increasing κ_{GM} causes an increase of the total phytoplankton, but a decrease of
 542 total zooplankton. The average size of the phytoplankton increases, and the Shannon
 543 index decreases, implying that the biomass shifts toward larger sizes. However, the only
 544 statistically significant correlation is for the average uptake in the DCM; with increas-
 545 ing κ_{GM} , the total uptake in the DCM decreases as the surface ocean gets more strat-
 546 ified. Overall, the slopes of most of the relationships are small, with low R^2 values.

547 Figures provided in the Supplementary information show substantial variability about
 548 the best fit line, suggesting nonlinear responses to changes in the eddy fluxes (see Fig-
 549 ures S10, S14, S17, S19). Quadratic fits can better explain the behavior in the average
 550 phytoplankton size across the domain with respect to κ_{GM} . There is also a slight decrease
 551 in the variance in the total biomass in the DCM and on the shelf, with diagnostics show-
 552 ing a local maximum in the domain, with non-negligible leading coefficients (see Figure
 553 S19). This indicates that there is a local maximum in the the size and biomass as κ_{GM}
 554 increases. A possible explanation for this could be that at low κ_{GM} , increasing the ef-
 555 fect of restratification increases the transport subsurface. However, with sufficient up-
 556 welling, this allows for the size and biomass to continue to increase. At high values of
 557 κ_{GM} , large stratification inhibits deep upwelling, decreasing the upwelled nutrient con-
 558 centration, total biomass in the surface and thus average phytoplankton size.

559 4.4 Offshore nutrient profiles

560 The nutrient restoring depth has strong impacts on the ecosystem behavior in the
 561 DCM. The total biomass of plankton in the DCM has strong, statistically significant neg-
 562 ative slope, implying that as the nutrient restoring depth deepens, the phytoplankton
 563 concentration decreases (see Figures 7 and S5). Additionally, the average size increases
 564 in the DCM, and the Shannon index decreases, implying that larger sizes out-compete
 565 smaller sizes in this region (see Figure S18). In the ecosystem model, we impose limits
 566 on minimum phytoplankton biomass. Thus the skew toward larger sizes may be explained
 567 by a combination of horizontal advection of large cells into the DCM and slow mortal-
 568 ity rates. The decrease in average uptake also supports this conclusion, as larger sizes
 569 have slower uptake rates. However, this phenomenon in our model requires further in-
 570 vestigation. On the shelf, the relationship between the nutrient restoring depth and tem-
 571 perature is statistically significant, with positive slopes implying that, as the nutricline
 572 deepens offshore, more plankton biomass remains at the surface as large phytoplankton
 573 out compete smaller phytoplankton (see Figure S15). The average size has a slightly neg-
 574 ative correlation, implying that the phytoplankton at the surface are overall smaller as
 575 the nutricline deepens as a consequence of reduced nutrient availability (see Figures S11
 576 and S12). A possible explanation for this could be that the source depth of upwelled wa-
 577 ters is deep enough to provide a sufficient source of nitrate to the surface.

578 The nutrient decay scale, which approximates the thickness of the nutricline, re-
 579 duces total plankton biomass in the DCM. However, the average size and the Shannon
 580 index in the DCM are not as sensitive to this parameter (Figure S18). In the SCM, the

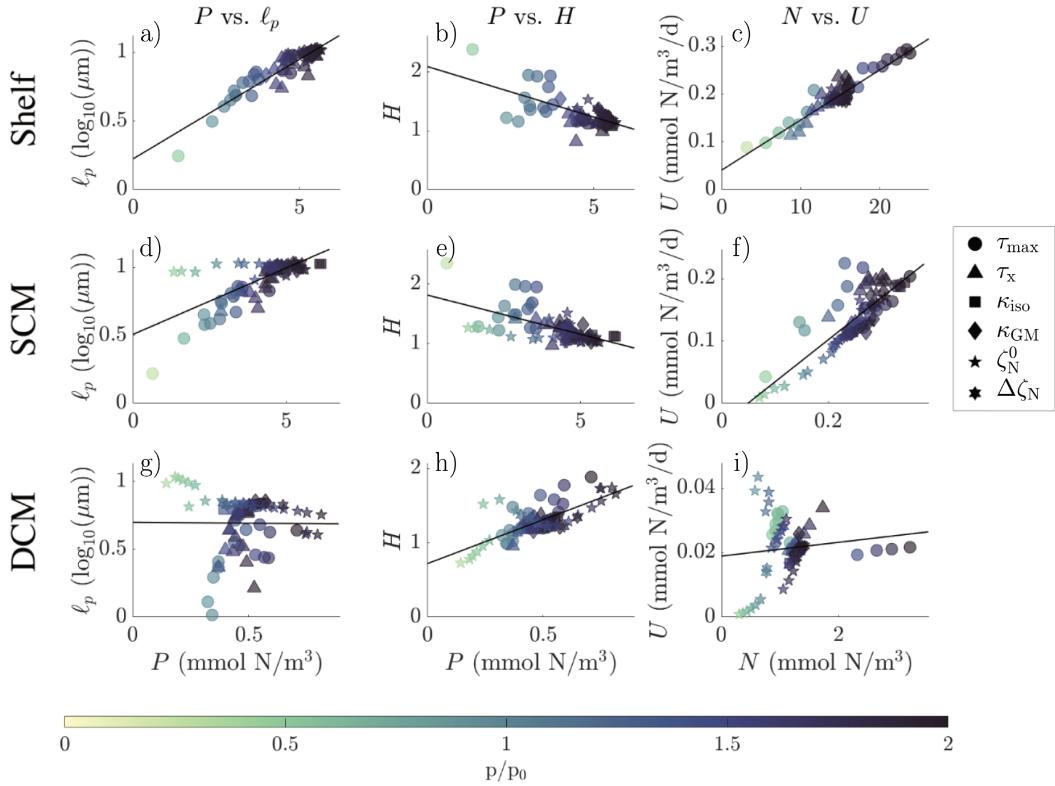


Figure 8: Relationships between measured concentrations of phytoplankton and size (a,d,g), phytoplankton biomass and Shannon Index (b,e,h), and nitrate and uptake by phytoplankton (c,f,i). These relationships are calculated on the shelf (a,b,c), the surface chlorophyll maximum (d,e,f), and in the deep chlorophyll maximum (g,h,i) across the entire suite of simulations. Marker shapes correspond to different control parameters, as indicated in the legend. The color of the marker is associated with the normalized magnitude of the corresponding control parameter, with darker colors indicating the larger values.

total plankton concentration decreases, likely driven by a decrease in total concentration of nitrate in source waters. This trend is further supported by a decrease in the average uptake (see Figure S12). While the total phytoplankton and zooplankton concentration decreases, the size distribution does not change significantly, or slightly decrease. At the SCM, there is a statistically significant decrease in the total phytoplankton concentration and total uptake reflecting lower nutrient concentrations in the source waters. We also observe a statistically significant decrease in the average phytoplankton size on the shelf and at the surface (Figure S15). However, the trends in phytoplankton biomass and nutrient uptake are not statistically significant.

4.5 Controls on ecosystem composition

Figure 8 shows the correlations between model diagnostics in the surface, SCM, and DCM. This comparison allows us to identify likely controls on ecosystem composition with respect to nutrient concentration and phytoplankton biomass.

On the shelf, we observe a linear relationship between the total phytoplankton concentration and the average size across our parameter sweeps. This indicates that as to-

596 tal phytoplankton concentration increases, the average size also increases, in agreement
 597 with previous studies (Taylor et al., 2012; Worden et al., 2004; Van Oostende et al., 2018;
 598 Moscoso et al., 2022). Similarly, as the total nutrient concentration varies on the shelf,
 599 the total uptake shows a linear response, increasing with nutrient concentration across
 600 our parameter sweeps. The Shannon Index, however, decreases with increasing phyto-
 601 plankton concentration. An increase in the average size, but a decrease in the Shannon
 602 Index indicate that the largest size class contributes most of the biomass on the shelf.
 603 The behavior is similar in the SCM. A major outlier occurs in the relationship between
 604 the total phytoplankton biomass and average size with respect to the nutrient restoring
 605 depth (see Figure 7). In the SCM, away from the region of strongest upwelling, the to-
 606 tal nutrient concentration is much smaller than the shelf concentration; however, the phy-
 607 toplankton biomass is approximately the same. This may be a consequence of Ekman
 608 transport in the surface mixed layer.

609 The total biomass and average size are not well correlated in the DCM. Similarly,
 610 the total nutrients and uptake are also not well correlated. A potential explanation for
 611 these responses is that the ecosystem composition in the DCM could be impacted by Ek-
 612 man transport or horizontal advection from the shelf or SCM, which would bring larger
 613 plankton and nutrients into the domain. The nutrient restoring depth parameter is a ma-
 614 jor outlier in the relationship between average size and plankton biomass in the DCM.
 615 In this parameter sweep, as the nutrient restoring depth deepens, while the total phy-
 616 toplankton concentration decreases, the average size increases (see Figure S6). A pos-
 617 sible explanation here is that a combination of low mortality and slow grazing rates would
 618 benefit larger phytoplankton, driving the shift in both size and biomass.

619 Additionally, we observe a wide scatter in the relationship between total nutrients
 620 and uptake in the DCM. The outliers in this relationship are in model solutions with higher
 621 offshore wind-stress curl. While the total uptake with respect to the wind-stress do not
 622 show major outliers (see Figure S5), the total nutrient concentration seems to be the rea-
 623 son for the large deviation in the trends. This may be a result of the strong intensity of
 624 upwelling, which would bring more nutrients to the surface, with nutrient intrusions into
 625 the DCM in regions of stronger upwelling.

626 We observe a strong, positive relationship between the total phytoplankton con-
 627 centration and the Shannon Index in the DCM, unlike in the SCM and on the shelf. Com-
 628 bining the relationships shown in Figure 8, this suggests that the Shannon index peaks
 629 when the phytoplankton concentration is approximately 1 mmol m^{-3} . In regions with
 630 lower phytoplankton biomass like the DCM, the average size is smaller than in the SCM
 631 and on the shelf (see Figure 5), with lower H , implying a few small size classes (Moscoso
 632 et al., 2022). As the total phytoplankton concentration increases, more size classes are
 633 able to emerge, expanding the diversity in the ecosystem. When the biomass increases
 634 above 1 mmol m^{-3} a larger proportion of the biomass is concentrated in the larger size
 635 classes, reducing diversity in the ecosystem.

636 5 Discussion

637 Strong productivity in EBUSs is driven by the upwelling of dense, nutrient rich wa-
 638 ter, which supports large phytoplankton blooms, and diverse ecosystems (Bakun & Nel-
 639 son, 1991; Chavez & Messié, 2009). In regions of high productivity, large phytoplank-
 640 ton contribute to most of the biomass (Hood et al., 1991). In contrast, in regions of low
 641 productivity, smaller phytoplankton dominate (Zubkov et al., 2000; Worden et al., 2004).
 642 While previous studies have identified patterns of ecosystem productivity and size, it is
 643 unclear which physical parameters impact plankton diversity and size structure the most,
 644 and to what extent. In this study, we conduct a systematic sensitivity analysis to de-
 645 termine the important controls of ecosystem productivity and diversity in an idealized
 646 EBUS tuned after the California Current System. We show that the ecosystem responses

647 in three dynamically distinct regions: the inner shelf, the surface chlorophyll maximum,
 648 and the deep chlorophyll maximum. While we do not explicitly have formulations of scal-
 649 ing laws for these ecosystem metrics with respect to the parameter sweeps at this time,
 650 this study serves as a starting point. The purpose of this study is to investigate a sub-
 651 set of physical parameters that can control plankton diversity and size structure in EBUSs.
 652 The relationships identified in this study are thus ideally suited to allow formulation of
 653 mechanistic scaling laws that relate physical drivers to ecosystem characteristics in EBUSs.

654 We find that changes in the wind stress maximum and the nutrient decay scale have
 655 the largest impacts on planktonic biomass. Previous work has identified that the mag-
 656 nitude of the offshore wind stress is responsible for setting the total upwelling nutrient
 657 fluxes (Bakun & Nelson, 1991; Chavez & Messié, 2009; Messié et al., 2009; M. G. Jacox
 658 et al., 2014, 2018; Fiechter et al., 2018). Through all three diagnostic regions in our model,
 659 we find that the phytoplankton biomass increases with the wind stress maximum as a
 660 consequence of increased upwelling (measured by a decrease in temperature on the
 661 shelf and in the SCM). On the shelf and in the SCM, phytoplankton show increasing up-
 662 take rates, but the total phytoplankton concentration exhibits saturating behavior, which
 663 can be explained by increased grazing by zooplankton (see Figures 7, and S3).

664 The offshore depth of the nutricline, ζ_N^0 , shows a similar trend as phytoplankton
 665 biomass, with an increase in productivity in the SCM and a decrease in the DCM with
 666 deepening nutricline. The diagnostic regions of the model are sensitive to the nutricline
 667 depth, with the SCM moving shore-ward, and the DCM deepening with increasing nu-
 668 tricline depths. The decrease in plankton biomass in the DCM can be explained by a deep-
 669 ening DCM, which would limit light penetration from the surface, reducing productiv-
 670 ity. The surprising response in this perturbation experiment is the increase in plankton
 671 biomass in the SCM. This trend may be explained by a shore-ward shift in the SCM,
 672 which would increase the total phytoplankton biomass as, $\bar{P}^{\text{surf}} < \bar{P}^{\text{shelf}}$, see Figures
 673 7, S1, and S3. Chavez & Messié (2009) note that shoaling of the nutricline in EBUSs in-
 674 creases offshore surface productivity. This response in the model can be seen in the lo-
 675 cation of the SCM, which has a large offshore extent with very shallow nutricline depths,
 676 and in the DCM, which moves toward the surface.

677 Previous work indicates that a combination of eddy advection and along-isopycnal
 678 mixing are responsible for surface nutrient subduction (Gruber et al., 2011; Colas et al.,
 679 2013). The studies conducted by Gruber et al. (2011) and Colas et al. (2013) used an
 680 eddy resolving regional model of the CCS (Gruber et al., 2006), and the Peru-Chile Sys-
 681 tem (Colas et al., 2012), with coupled eddy advective and diffusive fluxes. In our model,
 682 we are able to decouple these effects and study their consequences in isolation. Perhaps
 683 surprisingly, ecosystem properties appear very sensitive to perturbations in the isopy-
 684 cnal diffusivity, κ_{iso} . Variations in ecosystem properties with respect to κ_{iso} show strongly
 685 linear relationships that are highly statistically significant. Previous work has shown that
 686 eddies remove nutrients and other tracers from the surface, and subduct them beneath
 687 the euphotic zone (Gruber et al., 2011; Kessouri et al., 2020). The quantities that more
 688 directly reflect this eddy-driven mechanism are the total concentration of phytoplank-
 689 ton, the total concentration of zooplankton, and the uptake of nutrients by phytoplank-
 690 ton. Increased eddy stirring reduces the phytoplankton and zooplankton concentration
 691 at the surface, and suppresses uptake of nutrients. In the DCM, on the other hand, there
 692 is an increase of phytoplankton and zooplankton, with increased uptake rates, which may
 693 reflect the eddy-driven supply of nutrients to the subsurface by subduction. The impact
 694 on the average plankton size and ecosystem diversity in the SCM and DCM, however,
 695 is minimal, suggesting that ecosystem diversity may be predominantly controlled by the
 696 grazing dynamics internal to the ecosystem (Vallina et al., 2014).

697 The impact of eddy advective fluxes, however, does not align with previous stud-
 698 ies (Gruber et al., 2011; Colas et al., 2013). We find that variations in the buoyancy dif-
 699 fusivity, κ_{GM} in many cases have the opposite effect than the isopycnal diffusivity. For

example, the relationship between κ_{GM} and plankton biomass on the shelf has a local maxima within our parameter sweep, while the linear correlation of biomass at the surface is positive, while the correlation in the DCM is negative (see Figures 7, S1, S3, and S5). Thus, we suggest that eddy quenching is predominantly driven by eddy stirring along isopycnals.

With the exception of the wind stress maximum and the depth of the nutricline offshore, phytoplankton biomass between the SCM and DCM show nearly always opposite correlations. Phytoplankton biomass increases in the SCM and decreases in the DCM with narrower wind stress curl, a stronger eddy buoyancy diffusivity, and deeper nutriclines. The opposite behavior occurs with increasing isopycnal diffusivity. In the DCM, plankton biomass decreases; however, the potential mechanism for controlling this behavior has not been identified. Di Lorenzo (2003) and Rykaczewski & Checkley (2008) found that wider wind stress curl shoals isopycnal surfaces, which may impact the concentration of nutrients transported into the DCM. As a result, we may expect to see a shoaling of the DCM with smaller values of τ_x ; however, the physical locations of the diagnostic regions remain largely unchanged. This disagreement with previous work may arise from the lack of momentum advection in the physical model formulation – an important driver of interior upwelling in the absence of an along-shore pressure gradient (Lentz & Chapman, 2004; Gruber et al., 2011; M. J. Jacox & Edwards, 2011; Connolly et al., 2014). These anti-correlated behaviors between the SCM and DCM across multiple parameters may point to connectivity between these two diagnostic regions, but the mechanisms that control this behavior require deeper investigation.

While many of the behaviors found in this study are well described by linear relationships there are trends that may be better described through non-linear fits. Given our idealized framework, many of the linear responses seen in this study may have more non-linear effects in more comprehensive regional modeling frameworks. Figure S19 indicates the behaviors which may be better described by non-linear behaviors. The control parameters that exhibit the most non-linearity in our framework are the wind-stress maximum (Botsford et al., 2006; García-Reyes et al., 2014; M. G. Jacox et al., 2016), the eddy restratification Gruber et al. (2011); Renault et al. (2016). Specifically, the average size and total biomass may be better understood in non-linear relationships in both the maximum wind-stress and the eddy restratification.

In our study, we focus on a small number of drivers that have been shown or suggested to affect the ecosystem behavior in EBUSs. However, additional controls may influence ecosystem diversity in these regions, and call for future work. For example, we do not include variation in the thickness of the surface and bottom mixed layers. Within the surface layer, phytoplankton are vertically mixed and exposed to a variety of light conditions as a consequence of light attenuation (Sverdrup, 1953; Huisman et al., 1999; Obata et al., 1996; Mahadevan et al., 2012), which may be important in determining the ecosystem composition, specifically nearshore where surface and bottom mixed layer merge. In the absence of along-shore pressure gradients, upwelling is mostly constrained to the bottom boundary layer (Lentz & Chapman, 2004; M. J. Jacox & Edwards, 2011). Previous studies have shown that the thickness of the bottom boundary layer increases in the presence of upwelling favorable winds, which likely impacts the nutrient availability on the shelf and in the SCM (Trowbridge & Lentz, 1998; Perlin et al., 2005).

We do not explore variations in topography. The continental slope has been shown to influence the strength of upwelling (M. Jacox & Edwards, 2012; Lentz & Chapman, 2004), and the depth of the shelf may be important in controlling the vertical exchange of nutrients with the bottom boundary layer (Perlin et al., 2005).

MAMEBUS has the ability to explore the effect of idealized along-shore circulation, but we did not explore this component of the model. However, this may be impor-

tant for the transport of subpolar or subtropical waters with different nutrient contents, and the delivery of nutrients to the subsurface by the poleward undercurrent.

While we focus predominantly on the lower trophic ecosystem, our findings have the potential to inform studies of food-web diversity (Andersen et al., 2016; Stock et al., 2017). In EBUSs and other productive regions, high productivity, dominated by large phytoplankton sizes, generally supports short, productive food-webs (Chavez & Messié, 2009) and rich fisheries (Ryther, 1969). Along with identifying potential controls on plankton diversity in EBUSs, we also show the persistence of biomass quantization in the presence of horizontal heterogeneity under a range of physical regimes. Similar to the findings presented in Banas (2011), Vallina et al. (2014), and Moscoso et al. (2022), while plankton productivity appears to be controlled by the nutrient availability, species diversity – here manifest as size quantization – is controlled by the specialization of grazing behavior. While we focus on the impact of biophysical parameters on phytoplankton size structure, Cheresh & Fiechter (2020) found that other important biological variables such as pH and oxygen are predominantly modulated by the strength of the wind and the composition of source waters.

The relationships between ecosystem properties shown in Figure 8 provide new insight into the responses of multiple metrics of ecosystem diversity and productivity to more regularly measured quantities (e.g. phytoplankton biomass and nutrient concentration). These findings may be extended and tested in realistic three-dimensional regional modeling efforts, and guide the development of theoretical scalings that have the potential to characterize productivity and ecosystem structure as a function of a wide set of physical controls.

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Data Availability Statement: The DOI for the MAMEBUS code is <https://doi.org/10.5281/zenodo.3866652> (Stewart and Moscoso, 2020). This package includes the mamebus.c code along with example setup and processing functions that are used in MATLAB. See Moscoso et al. (2021) for additional model details.

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