Supporting Information for "Impact of spatial variability in zooplankton grazing rates on carbon export flux"

S. A. Meyjes[1], C. M. Petrik[2], T. Rohr[3,4], B. B. Cael[5], A. Mashayek[1]

[1]Department of Earth Sciences, University of Cambridge, Cambridge, UK

[2]Scripps Institution of Oceanography, University of California San Diego, La Jolla, CA, USA

[3]Institute for Marine and Antarctic Science, University of Tasmania, Hobart, Tasmania, 7000, Australia

[4]Australian Antarctic Program Partnership, University of Tasmania, Hobart, Australia

[5]National Oceanography Centre, Southampton, UK

References From the Supporting Information

Aumont, O., Ethé, C., Tagliabue, A., Bopp, L., & Gehlen, M. (2015). Pisces-v2: an ocean biogeochemical model for carbon and ecosystem studies. *Geosci. Model Dev*, *8*, 2465-2513. Retrieved from www.geosci-model-dev.net/8/2465/2015/ doi: 10.5194/gmd-8-2465-2015

Buitenhuis, E. T., Vogt, M., Moriarty, R., Bednaršek, N., Doney, S. C., Leblanc, K., ... Swan, C. (2013). Earth system science data maredat: towards a world atlas of marine ecosystem data. *Earth Syst. Sci. Data*, *5*, 227-239. Retrieved from www.earth-syst-sci-data.net/5/227/2013/Microzooplanktondatabase:

---

doi:10.1594/PANGAEA.779970AllMAREDATdatabases:http://www.pangaea.de/search?&q=maredat doi: 10.5194/essd-5-227-2013

Heneghan, R. F., Everett, J. D., Sykes, P., Batten, S. D., Edwards, M., Takahashi, K., ... Richardson, A. J. (2020, 11). A functional size-spectrum model of the global marine ecosystem that resolves zooplankton composition. *Ecological Modelling*, *435*, 109265. doi: 10.1016/J.ECOLMODEL.2020.109265

Lovato, T., Peano, D., Butenschön, M., Materia, S., Iovino, D., Scoccimarro, E., ... Navarra, A. (2022, 3). Cmip6 simulations with the cmcc earth system model (cmcc-esm2). *Journal of Advances in Modeling Earth Systems*, *14*. Retrieved from https://onlinelibrary.wiley.com/doi/full/10.1029/2021MS002814https://onlinelibrary.wiley.com/doi/abs/10.1029/2021MS002814https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2021MS002814 doi: 10.1029/2021MS002814

Moriarty, R., & O'Brien, T. D. (2013, 2). Distribution of mesozooplankton biomass in the global ocean. *Earth System Science Data*, *5*, 45-55. doi: 10.5194/ESSD-5-45-2013

Petrik, C. M., Luo, J. Y., Heneghan, R. F., Everett, J. D., Harrison, C. S., & Richardson, A. J. (2022, 11). Assessment and constraint of mesozooplankton in cmip6 earth system models. *Global Biogeochemical Cycles*, *36*. doi: 10.1029/2022GB007367

Rohr, T., Richardson, A. J., Lenton, A., & Shadwick, E. (2022, 11). Recommendations for the formulation of grazing in marine biogeochemical and ecosystem models. *Progress in Oceanography*, *208*. doi: 10.1016/J.POCEAN.2022.102878

Stock, C. A., Dunne, J. P., Fan, S., Ginoux, P., John, J., Krasting, J. P., ... Zadeh, N. (2020, 10). Ocean biogeochemistry in gfdl's earth system model 4.1 and its response to increasing atmospheric co2. *Journal of Advances in Modeling Earth Systems*, *12*. Retrieved from https://onlinelibrary.wiley.com/doi/full/10.1029/2019MS002043https://onlinelibrary.wiley.com/doi/abs/10.1029/2019MS002043https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2019MS002043 doi: 10.1029/2019MS002043

Stow, C. A., Jolliff, J., McGillicuddy, D. J., Doney, S. C., Allen, J. I., Friedrichs, M. A., ... Wallhead, P. (2009, 2). Skill assessment for coupled biological/physical models of marine systems. *Journal of Marine Systems*, *76*, 4-15. doi: 10.1016/J.JMARSYS.2008.03.011

Strömberg, K. H., Smyth, T. J., Allen, J. I., Pitois, S., & O'Brien, T. D. (2009, 8). Estimation of global zooplankton biomass from satellite ocean colour. *Journal of Marine Systems*, *78*, 18-27. doi: 10.1016/J.JMARSYS.2009.02.004

Westberry, T., Behrenfeld, M. J., Siegel, D. A., & Boss, E. (2008, 6). Carbon-based primary productivity modeling with vertically resolved photoacclimation. *Global Biogeochemical Cycles*, *22*, 2024. Retrieved from https://onlinelibrary.wiley.com/doi/full/10.1029/2007GB003078https://onlinelibrary.wiley.com/doi/abs/10.1029/2007GB003078https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2007GB003078 doi: 10.1029/2007GB003078

Yool, A., Palmiéri, J., Jones, C. G., de Mora, L., Kuhlbrodt, T., Popova, E. E., ... axy, A. Y. (2021). Evaluating the physical and biogeochemical state of the global ocean component of ukesm1 in cmip6 historical simulations. *Geosci. Model Dev*, *14*, 3437-3472. Retrieved from https://doi.org/10.5194/gmd-14-3437-2021 doi: 10.5194/gmd-14-3437-2021

Yool, A., Popova, E. E., & Anderson, T. R. (2013). Geoscientific model development medusa-2.0: an intermediate complexity biogeochemical model of the marine carbon cycle for climate change and ocean acidification studies. *Geosci. Model Dev*, *6*, 1767-1811. Retrieved from www.geosci-model-dev.net/6/1767/2013/ doi: 10.5194/gmd-6-1767-2013

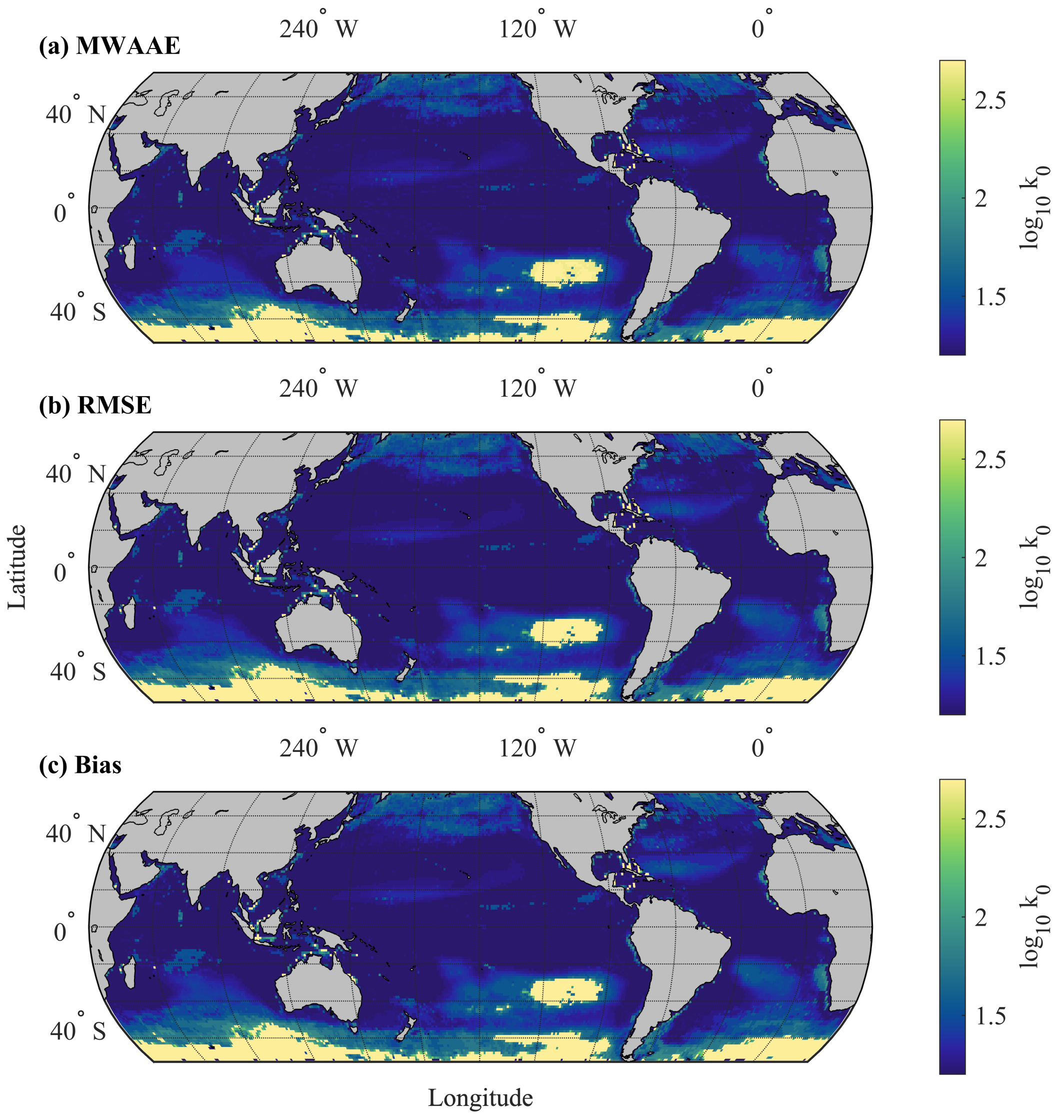

Figure S1. Locally-tuned microzooplankton half-saturation constant (k_0) estimated using alternate cost functions. a) MWAAE = Absolute average error (Stow et al., 2009) normalised using the observational mean instead of the standard deviation (as per the main article). b) RMSE = the Root Mean Squared Error (Stow et al., 2009), normalised by standard deviation of observations. c) Bias = Average Error or Bias (Stow et al., 2009), normalised by standard deviation of observations. Plots show very similar results are produced, no matter the cost function used.

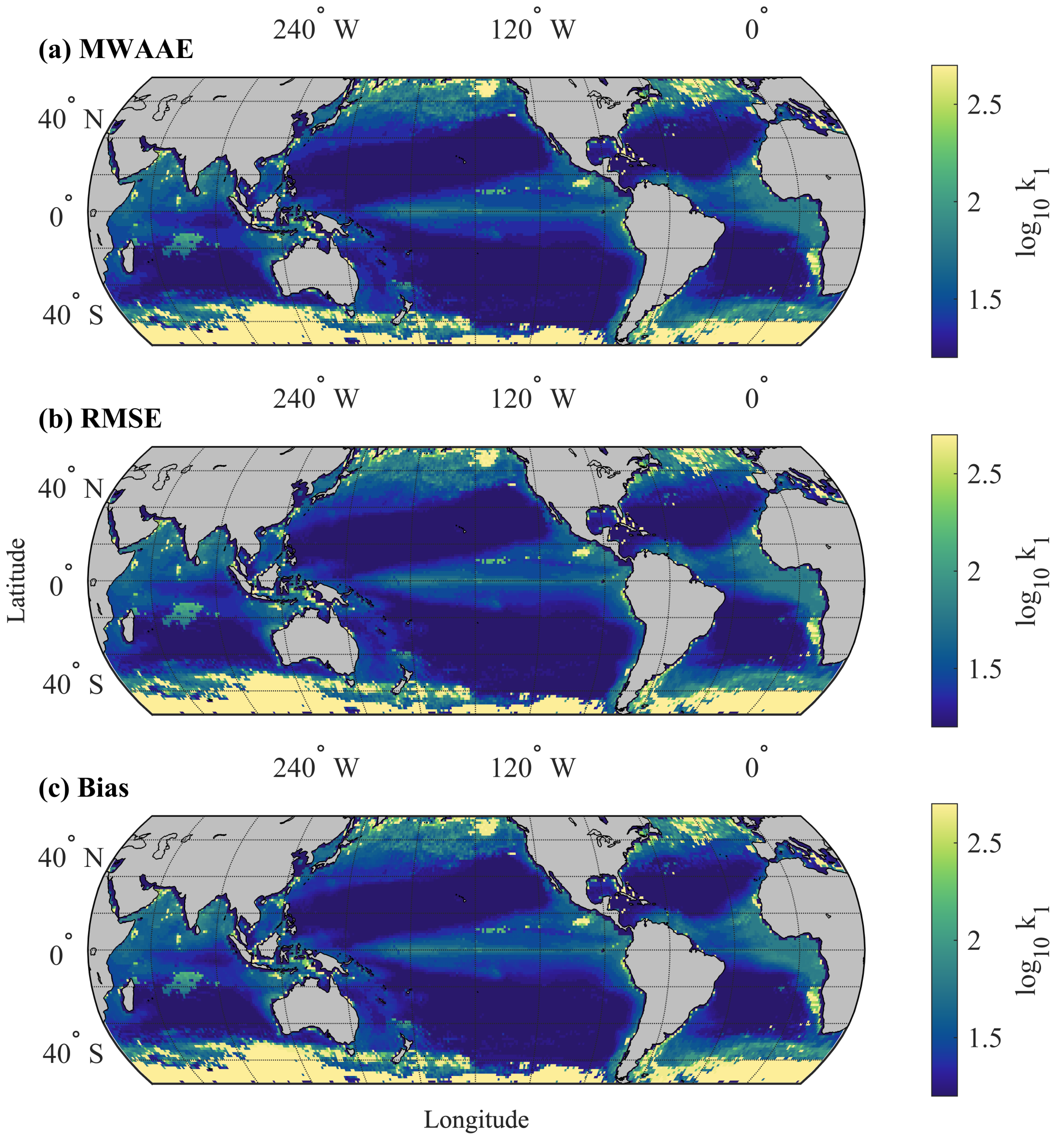

Figure S2. Locally-tuned mesozooplankton half-saturation constant (k_1) estimated using alternate cost functions. a) MWAAE = Absolute average error (Stow et al., 2009) normalised using the observational mean instead of the standard deviation (as per the main article). b) RMSE = the Root Mean Squared Error (Stow et al., 2009), normalised by standard deviation of observations. c) Bias = Average Error or Bias (Stow et al., 2009), normalised by standard deviation of observations. Plots show very similar results are produced, no matter the cost function used.

Table S1. Average locally-tuned microzooplankton (k_0) and mesozooplaknton (k_1) half-saturation constants estimated using alternate cost functions. Units are in mgC m^{-3}. MWAAE = absolute average error (Stow et al., 2009), normalised using the mean of observations. RMSE = the Root Mean Squared Error (Stow et al., 2009), normalised using the standard deviation of observations. Bias = annual average Error or Bias (Stow et al., 2009), normalised using standard deviation of observations.

Cost function	k_0		k_1	
	Median	Mean	Median	Mean
MWAAE	18	71	25	95
RMSE	18	72	29	95
Bias	18	73	28	93

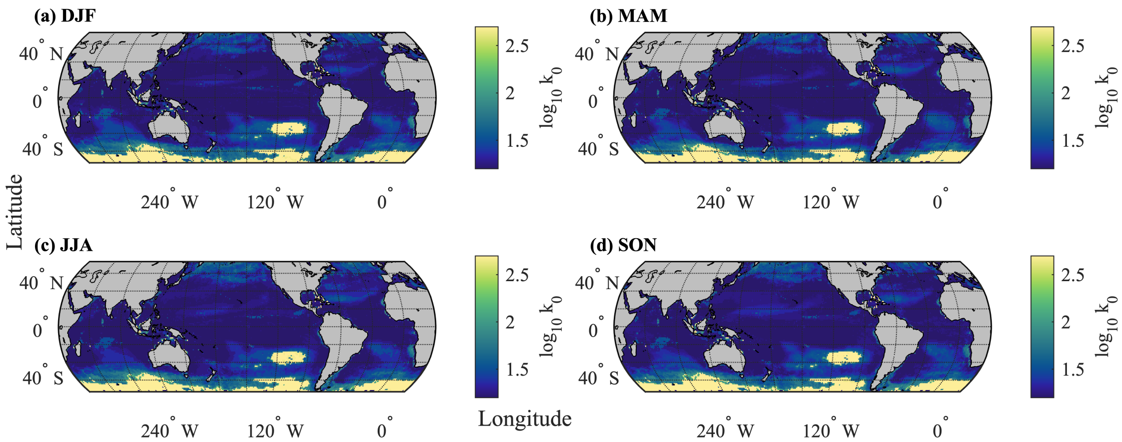

Figure S3. Locally-tuned microzooplankton half-saturation constant (k_0) estimated using nAAE cost function (Equation 12) from a) December-February, b) March-May, e) June-August and f) September-November. Figures show consistency across seasons.

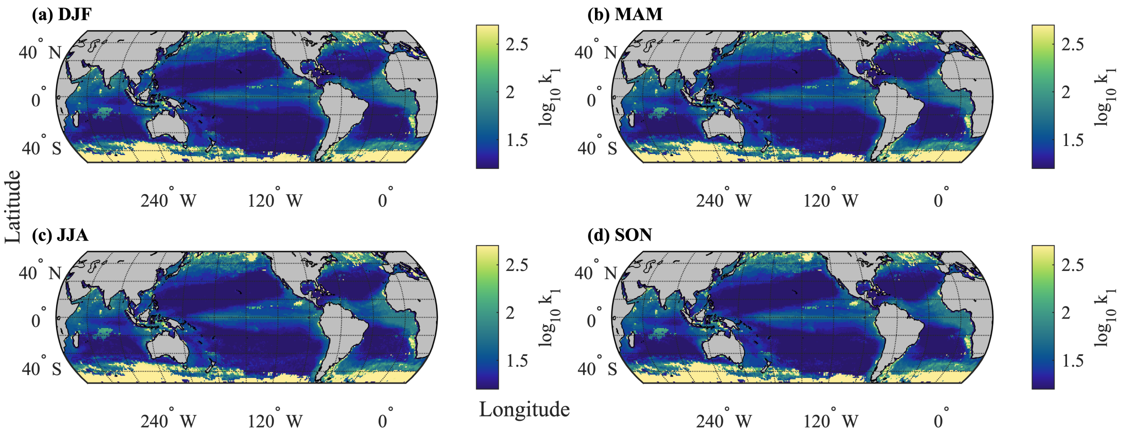

Figure S4. Locally-tuned mesozooplankton half-saturation constant (k_1) estimated using nAAE cost function (Equation 12) from a) December-February, b) March-May, e) June-August and f) September-November. Figures show consistency across seasons.

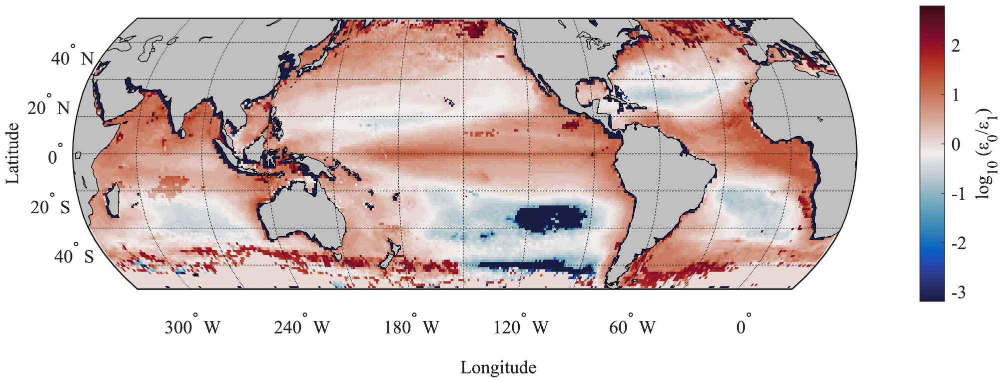

Figure S5. Prey capture efficiencies. Values represent the log ratio of prey capture efficiencies for micro- and mesozooplankton, or ε_0 and ε_1, respectively. The prey capture efficiency is calculated by dividing the maximum grazing rate (See Table 1) by the half-saturation constant for each grid cell (Rohr et al., 2022)

Table S2. Seasonal averages of locally-tuned microzooplankton (k_0) and mesozooplankton (k_1) half-saturation constants estimated using nAAE cost function (Equation 12). Units are in mgC m^{-3}.DJF= December-February, MMA=March-May, JJA = June-August and SON = September-November.

Season	k_0		k_1	
	Median	Mean	Median	Mean
DJF	18	72	29	94
MMA	18	71	29	95
JJA	18	72	29	93
SON	18	72	290	95

Table S3. Breakdown of mean cost estimates form the Local-k model run into its constituent parts (Equations 12-14). Cost consist of normalised Absolute Average Error values (nAAE) for each size class. Cost indicates model fit against satellite observations of phytoplankton biomass. A value of zero indicates a perfect match with satellite observations. DJF=December-February, MAM=March-May, JJA=June-August, SON= September-November, PS=nanophytoplankton, PL= microphytoplankton.

Time Period	AAE		nAAE		Cost
	PS	PL	PS	PL	
Annual	3.44	2.75	2.05	7.18	9.23
DJF	4.28	2.79	7.37	37.75	-
MAM	3.43	2.78	4.78	18.57	-
JJA	3.78	2.66	6.66	23.74	-
SON	4.18	2.76	4.02	18.95	-

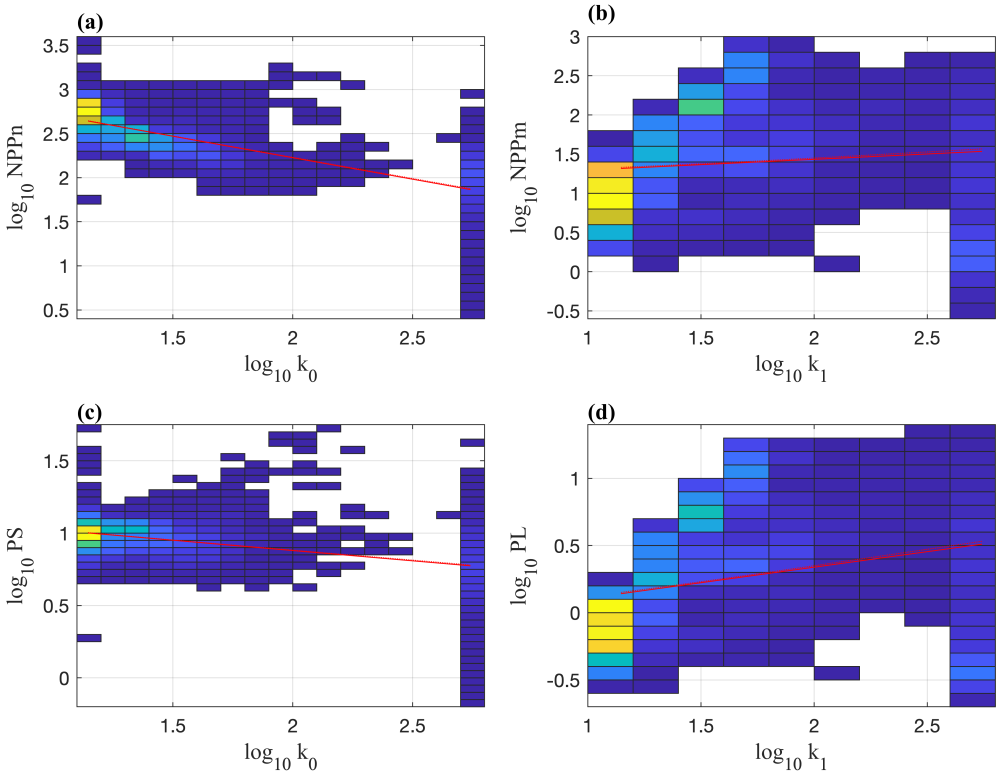

Figure S6. Comparison of half-saturation constant values from local optimisation with variables a) Microzooplankton half-saturation constant (k_0) and model-derived NPP from nanophyotplankton (NPPn), b) Mesozooplankton half-saturation constant (k_1) and model-derived NPP from microphytoplankton (NPPm), c) Microzooplankton half-saturation constant (k_0) and Nanophytoplankton Biomass (PS), d) Mesozooplankton half-saturation constant (k_1) and Microphytoplankton Biomass (PL). All values are log-transformed. Units are mgC m^{-3} for biomass and k values, and mgC m^{-2}d^{-1} for NPP. Red line = linear regression.

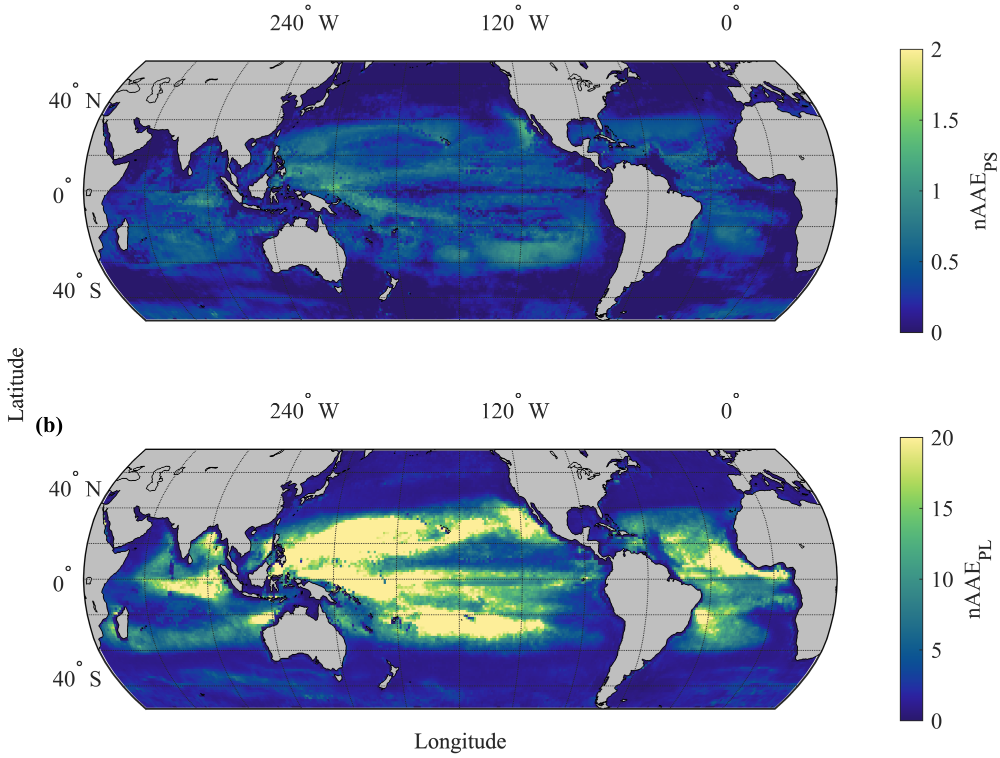

Figure S7. Cost values from the Local-k model are the sum of the a) Normalised Absolute Average Error for nanophytoplankton biomass, and the b) Normalised Absolute Average Error for microphytoplankton biomass.

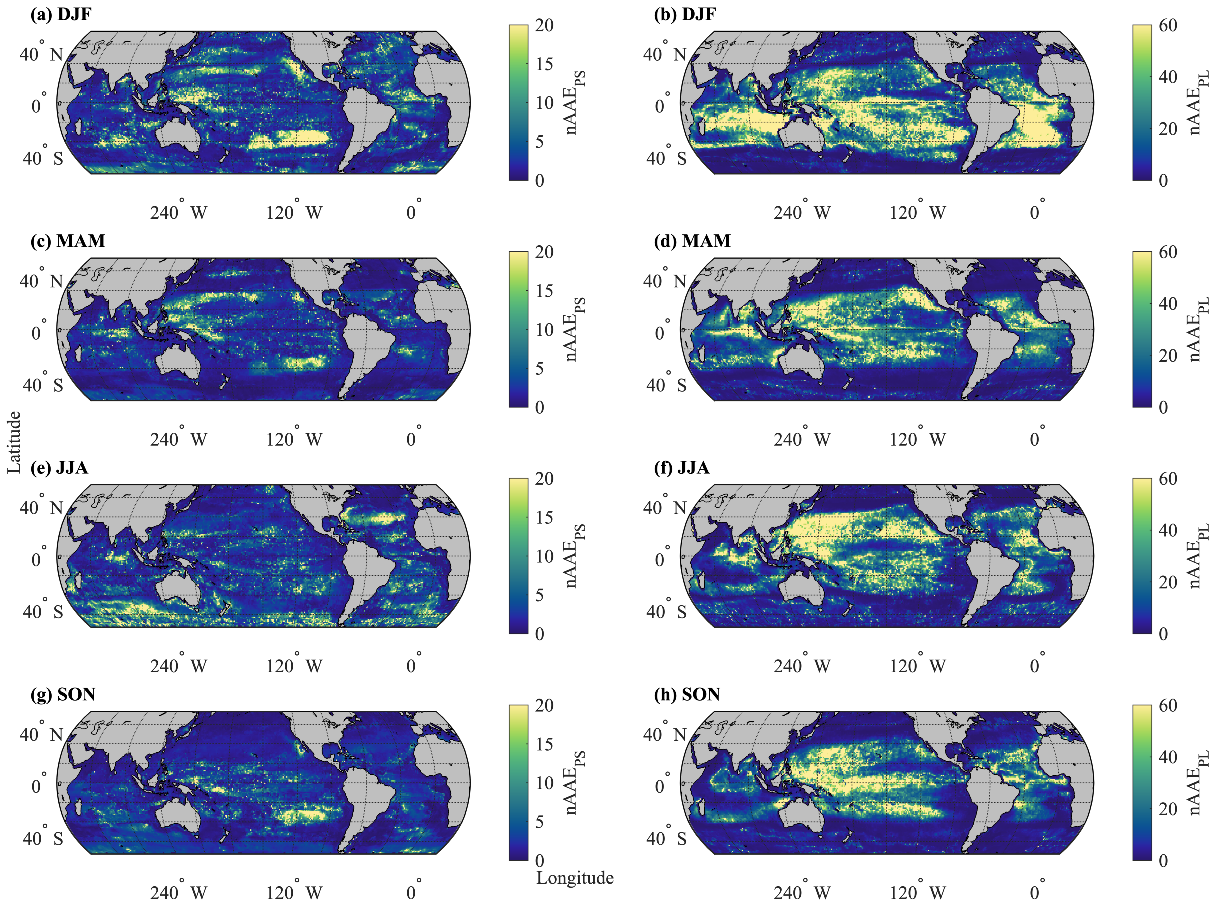

Figure S8. Normalised Absolute Average Error (nAAE) values for observations and model phytoplankton biomass estimates for each season. DJF = December-February. MAM = March-May). JJA = June-August. SON = September-November. Estimates are for both nanophytoplankton (a,c,e,g) and microphytoplankton biomass (b,d,f,h).

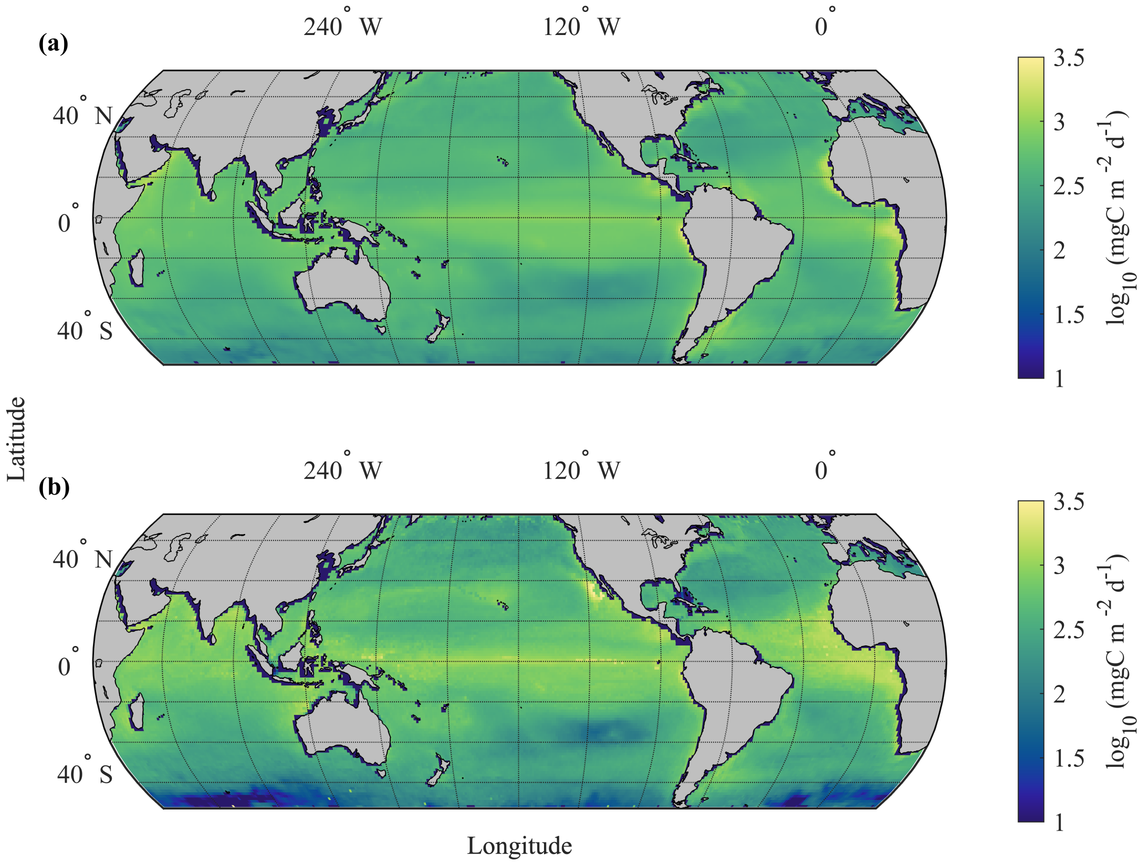

Figure S9. a) Local-k model Net Primary Productivity (NPP), b) Satellite-derived NPP from Westberry et al. (2008).

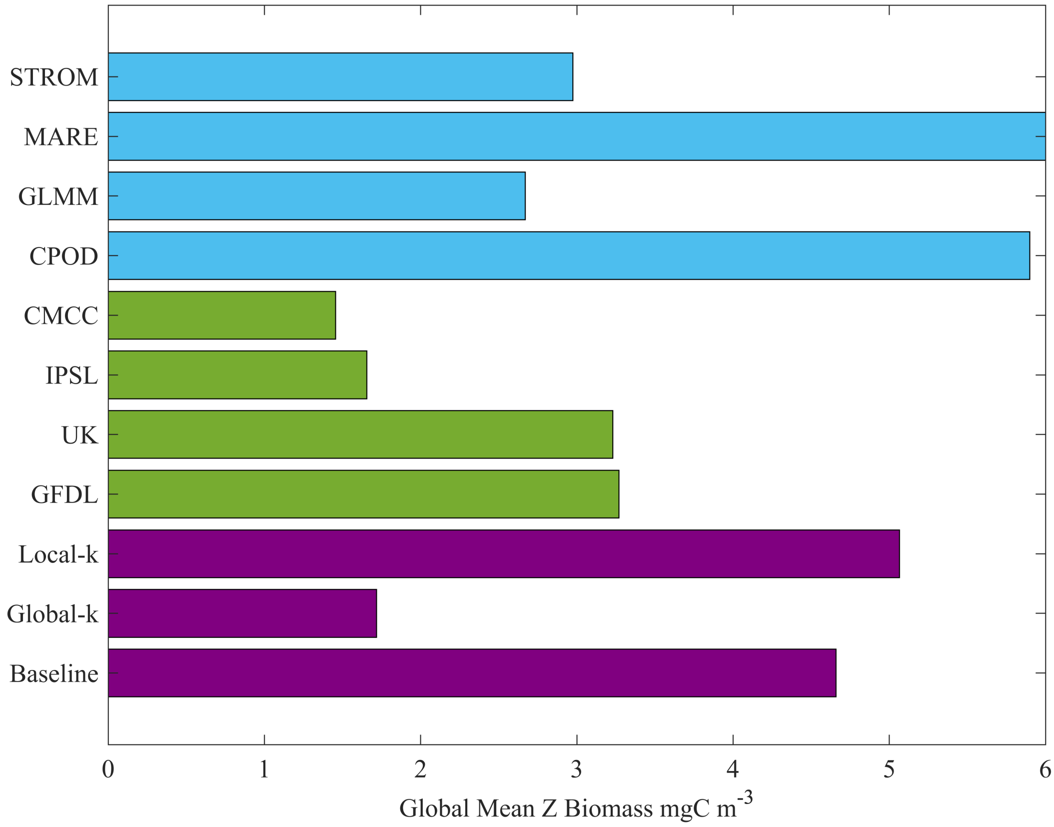

Figure S10. Global mean mesozooplankton (Z) estimates from this study, compared with other model and empirical values. Blue indicates estimates derived from observations. Green indicates model based estimates. Purple indicates estimates from this study from three different scenarios: Baseline scenario with non-otimised globally homogenous k values; Global-k scenario with globally optimised homogenous k value for each size class; Local-k scenario with locally optimised k values. Sources of data are: STROM= Strömberg et al. (2009); MARE= Buitenhuis et al. (2013); GLMM= Heneghan et al. (2020); CPOD=Moriarty and O'Brien (2013); CMCC= BFMv5.2 (Lovato et al., 2022); IPSL = PISCES2.0 model (Aumont et al., 2015), UK = MEDUSA2.1 model (Yool et al., 2013, 2021), GFDL = COBALTv2 model (Stock et al., 2020). See Petrik et al. (2022) for description of zooplankton estimates from other model and empircial estimates.

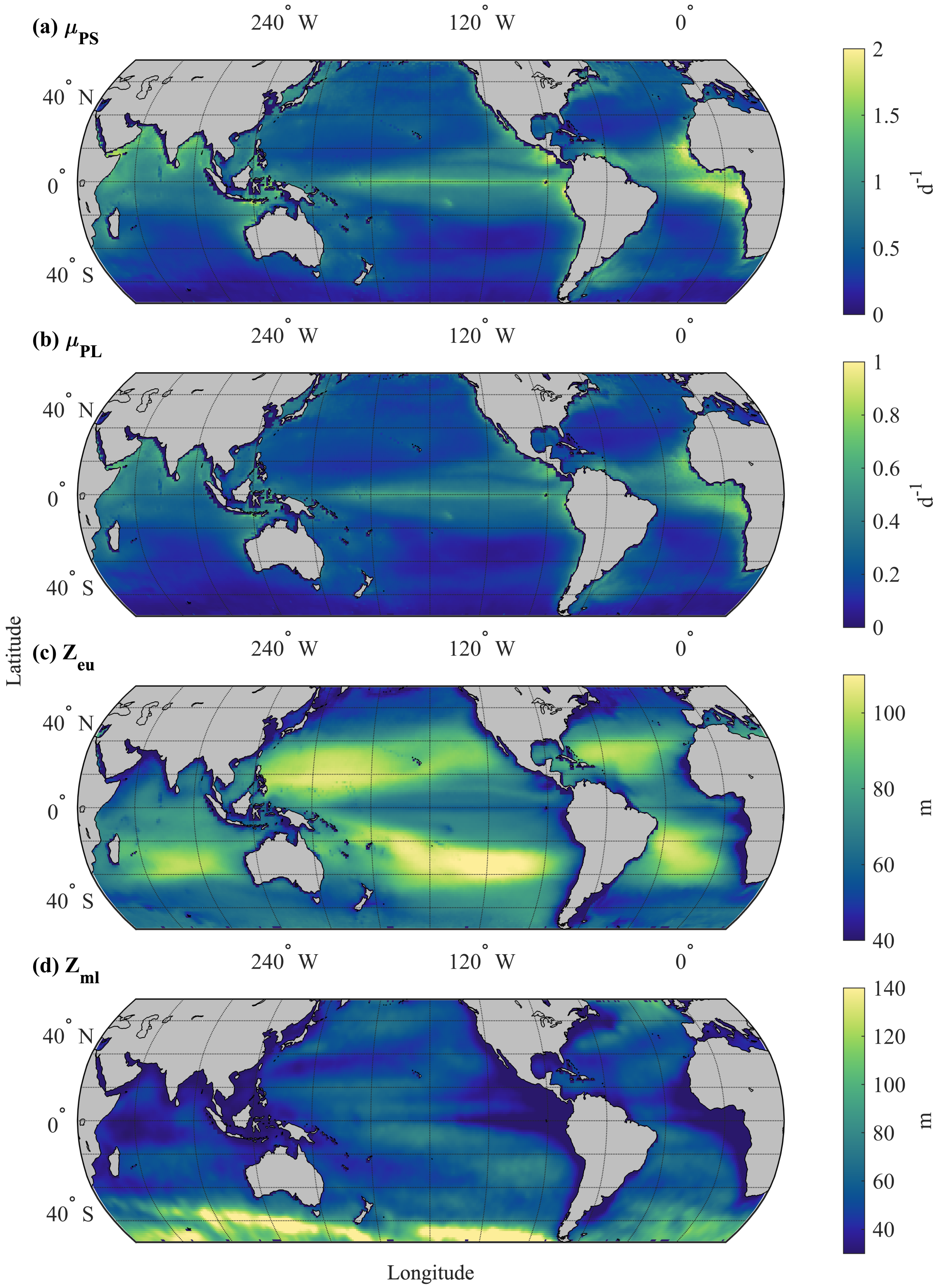

Figure S11. a) Local-k model nanophytoplankton growth rate, b) Local-k model microphytoplankton growth rate, c) Z_{eu}, depth of the euphotic layer, d) Z_{ml}, mixed layer depth. Note the different scales for the growth rate figures.

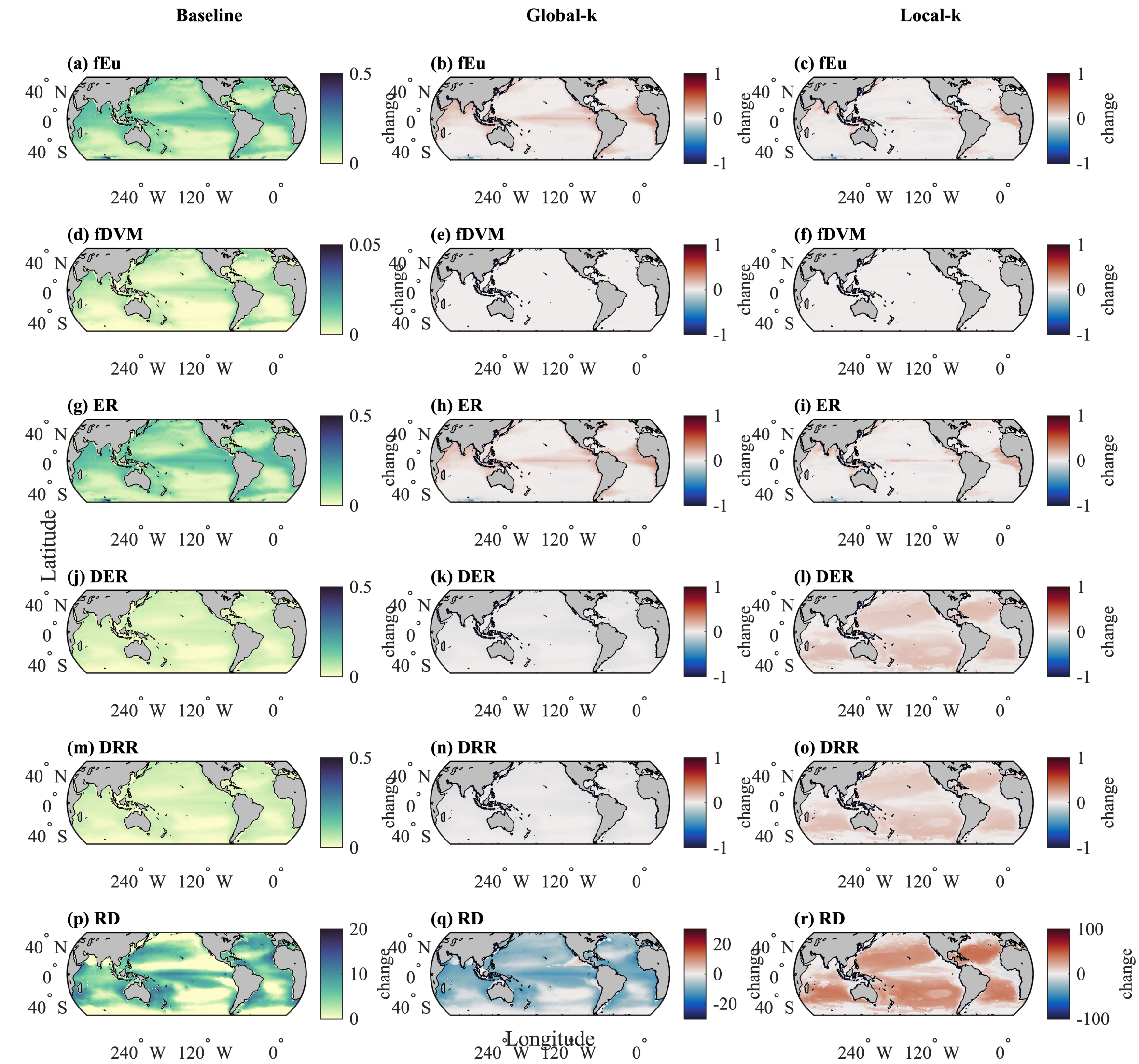

Figure S12. Changes in carbon export due to grazing parameterisation. Three model runs are presented: Baseline, Global-k and Local-k. The outputs from the Baseline run are presented in the left-hand column. Plots in the middle column show the absolute change when changing the model input from the baseline run (non-optimised k values) to the Global-k run (globally optimised k values). Plots in the righ column show the absolute change when changing the model input from the Global-k run (globally optimised k values) to the Local-k run (locally tuned k values). fEu = Total euphotic zone export flux as a fraction of NPP. fDVM = DVM-mediated export flux as a fraction of NPP. NPP = Net primary Productivity, ER= export ratio, DER=DVM export ratio, DRR= DVM respiration ratio. RD = Respiration Depression.

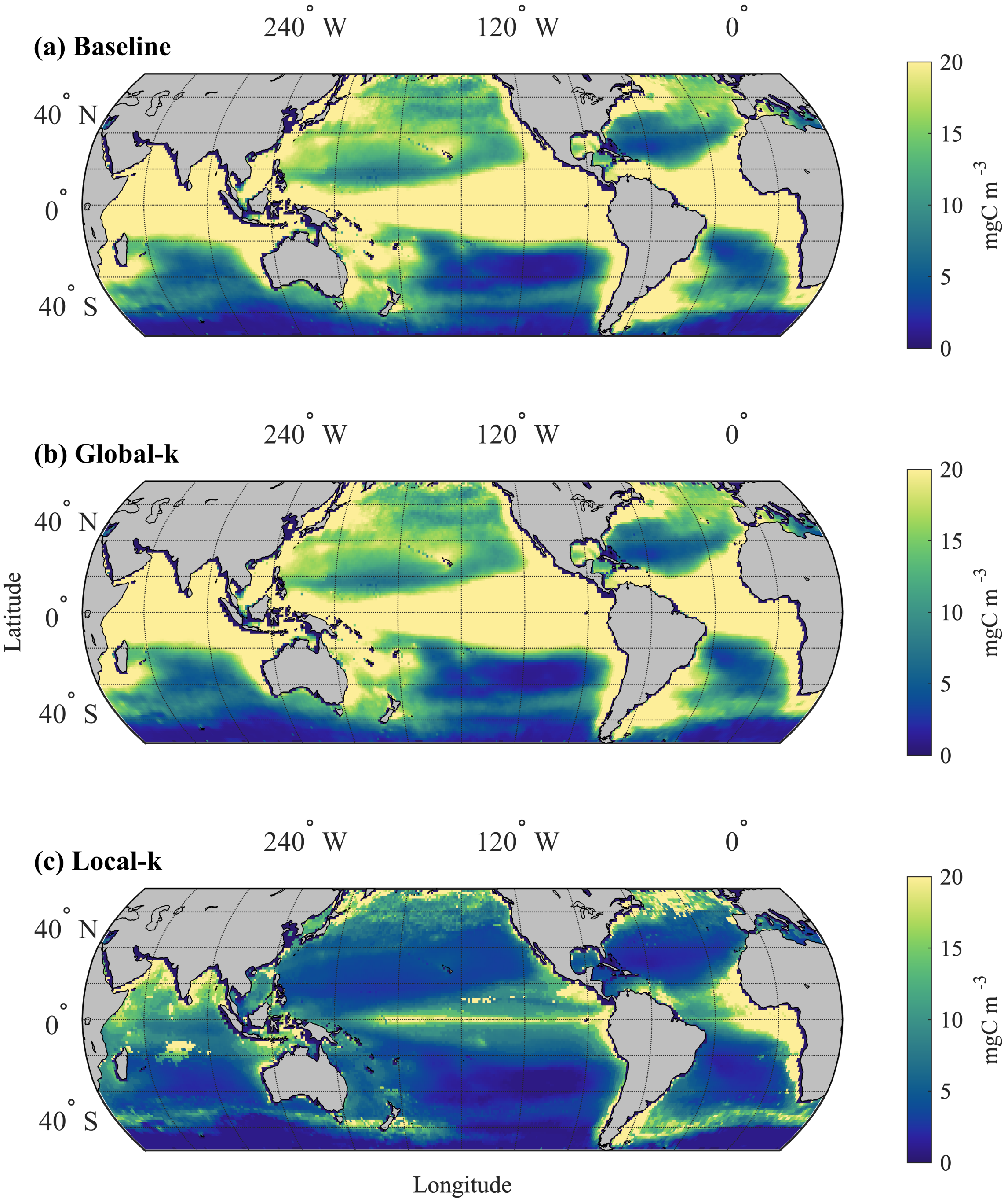

Figure S13. Microzooplankton biomass estimated by the model under three scenarios: Baseline, Global-k and Local-k.