Ocean biogeochemistry in the Norwegian Earth System Model version 2 (NorESM2)

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Abstract. The ocean carbon cycle is a key player in the climate system through its role in regulating atmospheric carbon dioxide concentration as well as other processes that alter the Earth's radiative balance. In the second version of the Norwegian Earth System Model (NorESM2), the oceanic carbon cycle component has gone through numerous updates that include, amongst others, improved process representations, increased interactions with the atmosphere, and additional new tracers. Oceanic dimethyl sulfide (DMS) is now prognostically simulated and its fluxes are directly coupled with the atmospheric component, leading to a direct feedback to the climate. Atmospheric nitrogen deposition and additional riverine inputs of other biogeochemical tracers have recently been included in the model. The implementation of new tracers such as 'preformed' and 'natural' tracers enables a separation of physical from biogeochemical drivers as well as of internal from external forcings and hence a better diagnostic of the simulated biogeochemical variability. Carbon isotope tracers have been implemented and will be relevant for studying long-term past climate changes. Here, we describe these new model implementations and present the evaluation of the model's performance in simulating the observed climatological states of water column biogeochemistry as well as in simulating the transient evolution over the historical period. Compared to its predecessor NorESM1, the new model's performance has improved considerably in many aspects. In the interior, the observed spatial patterns of nutrients, oxygen, and carbon chemistry are better reproduced, reducing the overall model biases. A new set of ecosystem parameters and improved mixed layer dynamics improves the representation of upper ocean processes (biological production and air-sea CO_2 fluxes) at seasonal time scale. Transient warming and air-sea CO_2 fluxes over the historical period are also in good agreement with observation-based estimates. NorESM2 participates in the Coupled Model Intercomparison Project phase 6 (CMIP6) through DECK (Diagnostic, Evaluation and Characterization of Klima) and several endorsed MIP-simulations.

1 Introduction

Up to the early 1990s, climate models consisted only of physical atmospheric general circulation models (AGCMs) with prescribed ocean surface state variables or simplified ocean modules (swamp ocean, slab ocean). As the ocean is a huge

reservoir and absorber of heat and of the greenhouse gas CO_2 (carbon dioxide), an expansion of climate models to include ocean components and a representation of the carbon cycle became a necessity. Coupled atmosphere-ocean-land models (now referred to as Earth System Models - ESMs) were eventually developed to account for further reservoirs and feedbacks including biogeochemical cycles (Bretherton, 1985; Cubasch et al., 2013; Heinze et al., 2019). The inclusion of the ocean carbon cycle is a first order requirement, because on timescales beyond a few decades, the ocean becomes the sole major sink for atmospheric excess CO_2 from anthropogenic emissions (Sarmiento and Gruber , 2006). ESM simulations can therefore be used to estimate historical carbon budgets and future partitioning of carbon fluxes into Earth system reservoirs under specified scenarios.

Today, modern ESMs are state-of-the-art tools utilized to study the complex interactions and feedbacks between various components in the Earth system in a comprehensive way (Flato et al., 2013). They are applied regularly to simulate climate evolutions across time scales and to study transient climate change, its drivers, and its impact on the environment (e.g., Bopp et al., 2013; Gehlen et al., 2014). By prescribing plausible scenarios of future emissions and land use, these models provide projections for possible future climate states. ESMs are typically upgraded every few years with new and improved process representations as well as adaptations to technical advancements (e.g., new hardware systems, higher resolution, etc.).

The ocean and its biogeochemistry play a crucial role in controlling the rate of anthropogenic climate change through a substantial negative feedback (Friedlingstein et al., 2006; Arora et al., 2013). However, the absorption rates of heat and carbon by the ocean are non-linear in space and time, due to the complex interactions with the internal climate variability (e.g., Tjiputra et al., 2012; Schwinger et al., 2014). Once passed the air-sea interface, the dissolved carbon dioxide reacts with seawater and is chemically transformed into different carbonate species. The ocean circulation and biological processes sequester parts of these into the deep ocean, where they stay isolated from the atmosphere, for decades to millennia (Sarmiento and Gruber , 2006). In addition to carbon dioxide, the ocean biogeochemistry also influences the Earth's climate through other seawater chemical constituents, such as dimethyl sulfide emissions. This could result in a number of feedback mechanisms within the Earth system that can either amplify or dampen the rate of climate change (Rhein et al., 2013). ESM projections are therefore critical for narrowing uncertainties in the future global carbon budget, and consequently its climate feedback.

ESMs have been increasingly used to estimate the evolution of marine ecosystem stressors, such as ocean acidification and deoxygenation, under anthropogenic climate change (e.g., Gehlen et al., 2014; Tjiputra et al., 2018). ESM applications to support climate policy-making, such as quantifying future compatible anthropogenic carbon emissions under a set of predefined scenarios as well as addressing emerging questions associated with the United Nations sustainable development goals have become more regular. With its growing relevance, a more realistic representation of the observed contemporary ocean biogeochemistry in Earth system models is urgently necessary to increase the fidelity of future projections.

In this manuscript, we present improvements in the ocean biogeochemical component of the Norwegian Earth System Model (NorESM). This component is based on the Hamburg Oceanic Carbon Cycle model (HAMOCC5.1), which was originally developed by Maier-Reimer (1993) and has gone through several development iterations (e.g., Six and Maier-Reimer, 1996; Maier-Reimer et al., 2005). At the Bjerknes Centre for Climate Research in Norway, the model has been branched off, further developed (Assmann et al., 2010; Tjiputra et al., 2010, 2013; Schwinger et al., 2016), and coupled to the Bergen Layered (isopycnic coordinate) Ocean Model (BLOM-iHAMOCC). Within the CMIP5 experiments, we have identified several shortcomings

in the previous model version of NorESM (NorESM1-ME, hereafter referred to as NorESM1). Here, we discuss several developments, relative to the NorESM1 version (described in Tjiputra et al., 2013), in the current model version (NorESM2, Seland et al., 2020), which contributes to CMIP6.

NorESM1 does not include interactively coupled DMS emissions from the ocean, which is the largest natural source of atmospheric sulfur, and contributes to aerosol and cloud formation. Instead, the atmospheric chemistry module of NorESM1 prescribed mean fixed climatology oceanic fluxes of DMS, and there is no feedback associated with climate-induced change in marine biological production. However, a model study has suggested that the inclusion of interactive DMS in future climate projection could potentially result in spatially-varying changes in warming rate and a non-negligible feedback on the climate system (Schwinger et al., 2017). This has prompted us to include a fully-interactive DMS cycle (production, emissions, and radiative impact) into NorESM2.

In the past years, the concept of emergent constraints was employed to identify key biogeochemical processes that lead to uncertanties in ESMs projections (e.g., Wenzel et al., 2014; Kwiatkowski et al., 2017). For instance, biases in the seasonal cycles of biological production and surface ocean pCO_2 have been identified as one of the factors contributing to the uncertainty in the projected carbon sinks and storage in the ESMs participating in CMIP5 (Kessler and Tjiputra, 2016; Goris et al., 2018). These studies motivate further improvement in the representation of biological processes, particularly focusing on the high latitude regions, such as the Southern Ocean. The biological improvements in NorESM2 were mainly achieved through tuning of the poorly constrained parameters in the ecosystem module.

In NorESM1, as well as other ESMs participating in CMIP5, there is a large uncertainty in the simulated interior oxygen concentration when compared to observations. This is partly attributed to the short model spin-up and bias in the interior remineralization processes (Cabré et al., 2015; Séférian et al., 2016). To alleviate this, we have tested several parameterizations of particulate organic carbon (POC) sinking schemes in our model (Schwinger et al., 2016). Currently, there are three different sinking schemes that can be selected in NorESM2. Based on our earlier assessments, we have used the scheme with sinking velocity that increases linearly with depth as the default parameterization in NorESM2.

Increasing atmospheric CO_2 and associated climate change will alter both the natural and anthropogenic components of ocean inorganic carbon chemistry. Disentangling future dynamical responses of these components separately is therefore needed to identify which processes (e.g., biological and physical, among others) regulate the simulated changes in ocean carbon storage today and in future. In NorESM1, only a single dissolved inorganic carbon (i.e., total DIC) tracer was implemented, and there is no suitably accurate method to separate between the driving mechanisms of its changes. In NorESM2, we have introduced a new 'natural DIC' tracer, which simulates changes in the natural component of DIC (i.e., it only interacts with fixed preindustrial CO_2 concentration during the air-sea gas exchange). Other key diagnostic tracers such as preformed phosphate, oxygen, and alkalinity have also been implemented, all of which allow us to better elucidate mechanisms driving the simulated ocean carbon chemistry changes (Bernardello et al., 2014). These tracers can also be used to infer interior ocean circulation-induced changes in biogeochemical tracers.

Nutrients are important constraints of ocean primary productivity and hence atmospheric carbon sinks. In NorESM1, the nutrient cycle was assumed to be an approximately closed system with a long-term loss due to sedimentation. The only external

source is through atmospheric nitrogen fixation and aerial dust deposition, which is converted into dissolved iron. Implementation of riverine input of nutrients in HAMOCC5.1 was initiated by Bernard et al. (2011) and a study by Gao et al. (in prep.) indicates that riverine nutrient inputs could improve the regional representation of marine biogeochemistry, with consequences for future projections, i.e., they increase coastal carbon sinks and alleviate nutrient limitations due to warming-induced

5 stratification. In NorESM2, we have accounted for riverine inputs of nutrients and other biogeochemical constituents. Other processes representing the external nitrogen sources such as atmospheric nitrogen deposition and nitrogen fixation have also been implemented and updated, respectively.

Since ESMs are used to project future climate change, questions have arisen whether or not these models are able to simulate past climate change. To this end, NorESM1 has been applied to study the sensitivity of climate states to different boundary

10 conditions in the past, going back from the last glacial to as far back as the mid-Pliocene (Zhang et al., 2012; Guo et al., 2019). The model was also used to study the sensitivity of the ocean carbon cycle to different background climates, which could provide insight into the ocean's role in regulating past atmospheric CO_2 variability (Kessler et al., 2018; Luo et al., 2018). There has also been a growing interest to determine if such complex models are able to reproduce climate states directly inferred from proxy-records. These paleo proxies, e.g., carbon isotopes ($\delta^{13}C$ and $\Delta^{14}C$), typically measured from foraminiferal

15 samples collected from seafloor sediment, are natural archives that store watermass properties and are used to infer large scale ocean circulation patterns as well as ventilation time scales during past climate changes (Peterson et al., 2014). In NorESM2, we have now implemented ^{13}C and ^{14}C tracers, which will be used as an additional ocean circulation and biogeochemistry constraint when simulating past climate variability.

Beyond the above mentioned biogeochemical processes, other improvements in tracer initialization, iron chemistry, air-sea

20 gas exchange parameterization, code readability, and documentations of the codes have been made. Moreover, there have been several updates within the physical ocean component of NorESM2 and a selection of these updates are discussed in this paper as they have direct impacts on the ocean biogeochemistry. In addition to describing the model improvements, we also evaluate the performance of the ocean biogeochemical component of NorESM2. Whenever possible, we compare and describe the performance of NorESM2 model with the first generation model, NorESM1.

25 The manuscript is organized as follows: advancements in the physics and more detailed descriptions of all improvements in biogeochemical processes are described in Section 2. Implementations of new tracers are presented in Section 3. The different model simulations performed and used in the paper are described in Section 4. In Section 5, we present results from our coupled ESM simulations as well as that of the ocean-only (preindustrial) simulation to illustrate the performance of the simulated carbon isotope tracers. Summary and discussion are presented in Section 6.

2 Model changes and improvements

2.1 General configuration changes

In NorESM2, the ocean-ice model adopts a tripolar grid instead of the bipolar grid of NorESM1. The tripolar grid was chosen because it is more isotropic at northern high latitudes and therefore is more efficient with respect to time integration (longer

time step) (Guo et al., 2019). Compared to NorESM1, NorESM2 has enabled a higher frequency ocean coupling to resolve the diurnal cycle in the flux- and state-exchange between ocean and atmosphere (i.e., hourly instead of daily atmosphere-ocean coupling). We also applied a full leap-frog time-stepping in both physical and ocean biogeochemical models to improve conservation of biogeochemical tracers (Schwinger et al., 2016).

5   There are several configuration options for NorESM2. For CMIP6, two configurations will mostly be used, differing only in the horizontal resolution of the atmospheric and land models with otherwise identical model components. They are named NorESM2-LM and NorESM2-MM and have atmosphere-land resolution of approximately 2° and 1°, respectively. In addition, both versions have a different parameter tuning in the atmospheric component, necessary to achieve a top of the atmosphere radiative balance under preindustrial conditions. Both NorESM2-LM and NorESM2-MM share the same ocean physical ocean

10   model (BLOM) and the same biogeochemical component (iHAMOCC) with a horizontal resolution of approximately 1°. The ocean model adopts 53 isopycnal layers with two non-isopycnic surface layers, which represent (1) the top 10 m depth and (2) the rest of the surface mixed layer. A more detailed description of the ocean physical component is provided in Bentsen et al. (in prep.). The ocean biogeochemistry performs similarly in both model versions. Unless explicitly specified, our analysis refers to the results from NorESM2-MM (hereafter referred to as NorESM2).

15   ## 2.2   Physical parameterizations

The simulated Atlantic Meridional Overturning Circulation (AMOC) strength in NorESM1 is on the strong side (30.8 Sv at 26.5°N; 1 Sv = 10^6 m^3 s^{-1}) compared to observation-based estimates and other CMIP5 models (Bentsen et al., 2013). The vigorous AMOC leads to a too warm and saline Atlantic Ocean at depth. Lack of upper ocean stratification at high latitudes is thought to contribute to this AMOC bias. Reformulating the eddy-induced transport (Gent and McWilliams, 1990) in order

20   to make it more efficient in the upper ocean non-isopycnic regime of the model and adjustments to the parameterized re-stratification by mesoscale eddies (Fox-Kemper et al., 2008) lead to improved high latitude stratification and a more realistic MLD, particularly at high latitudes.

NorESM1 has a cold bias in the depth range 200–1000 m between 50°S and 50°N (Bentsen et al., 2013) that could be related to insufficient upper ocean vertical mixing. Further, the new hourly atmosphere-ocean coupling and associated tuning of MLD

25   parameterizations lead to a cold bias in the Pacific equatorial thermocline that also indicates too little vertical mixing.

To improve this, two different approaches have been used. First, we allow surface turbulent kinetic energy (TKE) originating from wind stirring to penetrate below the mixed layer and be added to the TKE reservoir of the $k - \varepsilon$ turbulence model handling the shear instability mixing of the isopycnic interior. Secondly, with hourly atmosphere-ocean coupling, high frequency winds are available to parameterize wind work on near-inertial motions. Inspired by the approach of Jochum et al. (2013), a fraction of

30   this energy source is added to the mixed layer TKE reservoir, modifying the MLD estimation, while a fraction of the remaining energy is used to drive upper ocean mixing through assumed excitation and breaking of internal waves. Combining these approaches, we were able to reduce the above-mentioned upper ocean biases significantly. The mid-depth warm bias seen in NorESM1 is also reduced. More details on the physical improvements are described in Bentsen et al. (in prep.). As a result

of these improvements, NorESM2 simulates a more reasonable AMOC strength of approximately 21 Sv, which is within the range of the observational estimates of 17.9±3.3 Sv (Srokosz et al., 2012).

2.3 Dimethyl sulfide

NorESM2 prognostically simulates DMS concentration according to the formulation of Kloster et al. (2006), as follows:

$$\frac{\partial DMS}{\partial t} = S_{adv} + S_{prod} - S_{bac} - S_{uv} - S_{flux}, \tag{1}$$

where the first term on the right hand side denotes the physical transport, the second term denotes DMS production, and the third, fourth, and fifth terms denote sinks due to bacterial activity, photolysis, and flux to the atmosphere. The production term is computed as a function of temperature, pH, simulated detritus export production (opal and $CaCO_3$, implicitly computed as a function of silicate concentration):

$$S_{prod} = (\gamma_o \cdot export_{opal} + \gamma_c \cdot export_{CaCO_3}) \cdot \left(1 + \frac{1}{(T+10)^2}\right) \cdot (1 + (pH - pH_{pi}) \cdot \alpha). \tag{2}$$

The last term in Eq. 2 describes a pH-dependence of DMS production following (Six et al., 2013), which is parameterized based on the deviation of actual pH from the climatological monthly mean surface pH (pH_{pi}) calculated from the preindustrial control. Due to uncertainties in the pH-control on DMS production, we have omitted the pH-dependency term by setting α to zero in the presented simulations. Parameters γ_o and γ_c represent scaling factors for sulphur (S:Si and S:C) and are set to 0.025 and 0.125, respectively, such that DMS production is more sensitive to $CaCO_3$ production in the model. This assumption is due to the fact that haptophyte-class phytoplankton generally has a higher DMSP to cell carbon ratio than diatoms (Keller et al., 1989). Since the opal and $CaCO_3$ portions of export production are implicitly computed as a function of silicate concentration, e.g., opal ($CaCO_3$) production is high (low) when surface silicate is abundant and vice versa, the DMS production is also sensitive to the long-term trend in the silicate concentration.

The DMS sink due to bacteria consumption is estimated as a function of temperature [°C], DMS concentration, consumption rate (γ_{bac}=0.0864 day^{-1} °C^{-1}), and a half-saturation constant (k_{cb}=10 nmol L^{-1}), as follows.

$$S_{bac} = \gamma_{bac} \cdot (T + 3.0) \cdot DMS \cdot \left(\frac{DMS}{k_{cb} + DMS}\right). \tag{3}$$

The DMS photolysis term is defined as a function of photolysis rate (γ_{uv}=0.0011 $m^2(Wday)^{-1}$), incoming shortwave radiation attenuated by water and phytoplankton, I_z, and DMS concentration:

$$S_{uv} = \gamma_{uv} \cdot I_z \cdot DMS. \tag{4}$$

Lastly, in NorESM2, the atmospheric model receives the DMS emissions (S_{gas}) that are prognostically computed by the ocean biogeochemistry model (see Section 2.8).

2.4 Riverine input

The influx of carbon and nutrients from over 6000 rivers to the coastal oceans has been implemented based on previous work of Bernard et al. (2011) with modifications. Bernard et al. (2011) have implemented the riverine fluxes based on the levels in

year 1995, provided by an early version of the Global-NEWS model (Seitzinger et al., 2005). In addition to the riverine DIC, dissolved organic carbon (DOC), inorganic nitrogen and phosphorus, particulate organic carbon (POC), particulate nitrogen and phosphorus, and dissolved silicate, we have also included riverine alkalinity (ALK) and iron (Fe). Except for DIC, ALK and Fe, all data are provided by the more recent Global-NEWS2 model (Mayorga et al., 2010), which is a hybrid of empirical,

5 statistical and mechanistic model components that simulate steady-state annual riverine fluxes of carbon and nutrients. The DIC and ALK fluxes are taken from the work by Hartmann (2009). Riverine Fe-flux is calculated as a proportion of global gross dissolved Fe input of 1.45 Tg yr^{-1} (Chester, 1990), weighted by water runoff of each river. Only 1% of the riverine dissolved Fe is added to the oceanic dissolved Fe, since approximately 80 to 99% of the fluvial gross dissolved Fe is removed during estuarine mixing (e.g., Sholkovitz et al., 1981; Shiller and Boyle, 1991; Bruland and Lohan, 2014). Instead of releasing

10 the riverine fluxes to the nearest ocean grid cell (Bernard et al., 2011), we have interpolated all fluxes at river mouths in the same way as the freshwater runoff (distributed as a function of river mouth distance with e-folding length scale of 1000 km and cutoff of 300 km) to the ocean grid. The fluxes are specified to be constant over time at contemporary levels (year 2000). In our model, the organic form of dissolved carbon (DOC) is connected to nutrients through the Redfield ratio (C:N:P=122:16:1), and therefore other forms of dissolved organic matters (e.g., DON, and DOP) are not explicitly simulated. Since Global-

15 NEWS provides estimates of dissolved organic matter in carbon, nitrogen, and phosphate forms (DOC_{riv}, DON_{riv}, and DOP_{riv}, respectively) separately, only the minimum of the three riverine dissolved organic constituents is added to the DOC term in the model (i.e., $DOC = DOC + min(DOC_{riv}, r_{C:N} \cdot DON_{riv}, r_{C:P} \cdot DOP_{riv})$). Any excess or remaining organic matter of the three constituents is then added to the corresponding inorganic pools (DIC, NO_3 or PO_4). The same concept also applies to riverine inputs of particulate organic carbon (POC) (see also Bernard et al., 2011).

20 **2.5 Atmospheric nitrogen deposition**

We apply anthropogenic nitrogen deposition fluxes that potentially affect the simulated ocean carbon uptake (through an increase of the available nitrate for biological production) to the ocean biogeochemical model. The monthly input fields, spanning the years 1850-2014, are simulated by chemistry transport models and provided by CMIP6 (Jones et al., 2016). Conservative remapping is used to interpolate the input data from a regular 2.5°x1.9° latitude-longitude grid to the tripolar

25 ocean model grid of NorESM2. Four species of wet or dry and oxidized or reduced nitrogen deposition rates are included in the input fields. All of them are added to the nitrate pool in the top-most ocean layer.

2.6 Particle export

In NorESM1, the export of particulate organic matter is parameterized with a constant sinking speed and a constant reminer-alization rate at depth, when sufficient oxygen is available. This simplistic formulation has been shown to have difficulty in

30 accurately representing the observed particle fluxes at depths (Kriest and Oschlies, 2008) and leads to biases in the interior distributions of biogeochemical tracers (e.g., as seen from remineralized phosphate concentrations). In NorESM2, we have developed two additional particle flux parameterizations that can be selected. They are referred to as WLIN and AGG schemes. The WLIN scheme is similar to the standard scheme but the sinking speed is a linear function of depth: $w_{POC} = min(w_{min}+az,$

w_{max}). Here, we use $w_{min} = 1\ md^{-1}$, $w_{max} = 60\ md^{-1}$, and $a = 60/2400\ md^{-1}m^{-1}$. When w_{min} and w_{max} are set to zero and infinity, respectively, this scheme is equivalent to the widely used Martin-curve formulation (Martin et al., 1987).

The AGG scheme implements a prognostic sinking speed, calculated according to a size distribution of sinking particles. The total concentration of particulate matter, formulated as a function of phytoplankton and detritus, forms sinking aggregates with explicitly computed size distribution that follows a power-law formula (Kriest and Evans, 1999; Kriest, 2002):

$$n(d) = Ad^{-\beta}, \quad l < d < \infty. \tag{5}$$

Here, d represents the particle diameter and A and β represent parameters of the size distribution. The minimum particle diameter l is set to 0.002 cm. The sinking speed of aggregates is computed according to the diameter of each aggregate. More details of the implementation of the AGG formulation are described in Schwinger et al. (2016). Based on the performance of the different schemes, we have set WLIN to be the default scheme and it is used in all experiments presented here. More details on the differences in the simulated interior biogeochemistry using the different particle export schemes are available in Schwinger et al. (2016).

2.7 Nitrogen fixation

Nitrogen fixation by cyanobacteria is computed implicitly and directly converted into nitrate concentration. In NorESM1, nitrogen fixation is implemented such that it can occur anytime and anywhere in the surface ocean as long as the nitrate concentration is lower than phosphate (multiplied by the stoichiometric nitrate to phosphate ratio $R_{N:P}$) following Maier-Reimer et al. (2005). However, Breitbarth et al. (2007) provided some evidence that the large scale distribution of *Trichodesmium*, a type of cyanobacteria, is well constrained by seawater temperature between 20 and 30°C. Based on this, a temperature-dependent function $f(T)$ according to Kriest and Oschlies (2015) has been added to the nitrogen fixation formulation in NorESM2. The rate of change of nitrate owing to nitrogen fixation is formulated as follows:

$$\frac{\partial NO_3}{\partial t} = f(T) \cdot \mu \cdot max(0, R_{N:P} \cdot PO_4 - NO_3), \tag{6}$$

with

$$f(T) = max \left(0, \frac{-0.0042 \cdot T^2 + 0.2253 \cdot T - 2.7819}{0.2395} \right), \tag{7}$$

where μ is the maximum N_2 fixation rate (0.005 day^{-1}). In addition, for each mole of N fixed to nitrate, 1.25 moles of dissolved oxygen and 1 mole of alkalinity are consumed and lost in the surface layer. The corrected formula essentially limits the occurrence of N-fixation to warm low latitudes.

2.8 Air-sea gas exchange

In NorESM2, the air-sea gas exchange of CO_2, O_2, N_2, N_2O, DMS, CFC-11, CFC-12, and SF_6 is computed prognostically according to the updated formulation of Wanninkhof (2014). Here, the air-sea flux F of gas X is computed as a function

of surface wind speed U, Schmidt number Sc, gas solubility K_o, and partial pressure difference of gas X, based on a bulk formulation:

$$F_X = 0.251 \cdot U^2 \cdot (Sc/660)^{-0.5} \cdot K_o \cdot (pX_{sw} - pX_{air}). \tag{8}$$

The net fluxes are computed for the top layer of the ocean model (i.e., 10 m depth). The updated formulation includes a refitted temperature-dependent Schmidt number that can be applied for a temperature range of -2 to 40°C. The solubility of all gases is computed as a function of surface temperature and salinity following Weiss (1970) for O_2 and N_2, Weiss and Price (1980) for CO_2 and N_2O, Warner and Weiss (1985) for CFC-11 and CFC-12, and Bullister et al. (2002) for SF_6. The flux of DMS is only unidirectional (outgassing; $pDMS_{air} = 0$).

In the historical simulation, we use the annual atmospheric concentrations of CFC-11, CFC-12, and SF_6, divided into northern and southern hemispheric values, according to Bullister (2014). For the atmospheric CO_2 concentration, monthly global-mean values from the CMIP6 dataset are used. In the preindustrial simulation, a constant CO_2 concentration of 284.32 ppm is used.

2.9 Dissolved iron parameterization

Adjustments in the iron parameterization have been made to ensure that NorESM2 simulates the observed iron-limited primary production in the Southern Ocean, Equatorial and North Pacific. In the model, the consumption and release of dissolved iron associated with biological activities are determined using a fixed stoichiometry ratio ($R_{Fe:P} = 6.1\text{e-}4$ mol Fe mol P^{-1}, previously $3.7\text{e-}4$ mol Fe mol P^{-1}). In the surface layer, a constant fraction ($3.13\text{e-}6$ kmol Fe kg^{-1} day^{-1}, previously $6.27\text{e-}6$ kmol Fe kg^{-1} day^{-1}) of aerial dust deposition (Mahowald et al., 2005) is instantaneously converted into bio-available iron. The updated global input of bio-available iron from the atmosphere is 2.8 Gmol Fe yr^{-1}, which is within the range of values used by other models (Tagliabue et al., 2016). Finally, throughout the water column, complexation of iron by organic substances (ligands) is assumed:

$$\frac{\partial Fe_{cmpl}}{\partial t} = -\lambda_{Fe} \cdot max(0, Fe - Fe_o), \tag{9}$$

where the strength of this complexation λ_{Fe} is set to 0.05/365 (previously 0.005/365) day^{-1} and the threshold Fe_o has been reduced from 0.6 to 0.5 nmol Fe m^{-3}. The latter is motivated by the fact that the observed iron concentration in the deep Southern Ocean is lower than 0.6 nmol Fe m^{-3} (Boyd and Ellwood, 2010). The higher complexation rate leads to a faster relaxation toward this value.

2.10 Ecosystem parameterization updates

The underlying marine ecosystem parameterization in NorESM2 remains the same as in NorESM1, but many of the parameters have been adjusted to reduce biases that are present in NorESM1. The main deficiencies of the spatial annual mean primary productivity pattern in NorESM1 are a too strong primary production (PP) in the Southern Ocean, the Eastern Tropical Pacific, and to a lesser degree the North Atlantic, contrasted by a very low PP in the subtropical gyres (most pronounced in the Pacific).

The high productivity in the high latitudes is accompanied by an exaggerated annual cycle of PP showing a too strong spring bloom and a too fast decline of PP afterwards. Tuning of the ecosystem parameterization during the development of NorESM2 was focused on improving these regional shortcomings. The changes in ecosystem parameters listed in Table 1 mainly serve two purposes: (i) to increase top-down limitation by zooplankton grazing during phytoplankton peak bloom (but not before and after), and (ii) to increase the fraction of nutrients that is routed through dissolved organic matter (DOM).

The first point is achieved through a reduction in zooplankton mortality as well as increases in the maximum grazing rate, assimilation efficiency, and half-saturation constant for zooplankton grazing. The latter point is mainly achieved by reducing the production of detritus by zooplankton (fecal pellets, $1 - \varepsilon_{\text{zoo}}$ of grazing) and increasing exudation and excretion rates. This allows, in combination with a decrease of the DOM remineralization constant, more nutrients to be laterally transported out of regions where nutrient trapping occurs, i.e., the Tropical Pacific.

Additionally, $CaCO_3$ and silicate to phosphate ratios were tuned to remove the high alkalinity bias of NorESM1 (see Schwinger et al., 2016, for details). Note that some adjustments of parameters given in Table 1 were also necessary because of the new sinking scheme (increasing sinking speed with depth, see Section 2.6), and the different physical circulation fields between NorESM1 and NorESM2. An updated schematic diagram of the marine ecosystem module in NorESM2 is presented in Fig. 1.

In NorESM1, biological productivity was computed only for the top 100 m depth, which presumably represents the averaged euphotic layer. In an isopycnic model, there is no static interface separating this depth level. In cases where the bulk MLD extends below 100 m, we virtually split this at 100 m and the biological production is simulated only down to this interface. In NorESM2, we have omitted this virtual layer splitting and the biological production is allowed to occur below 100 m as long as it is within the bulk mixed layer depth and has sufficient light (attenuated with depth and chlorophyll concentration) for phytoplankton growth.

3 New tracers

3.1 Preformed tracers

Four new preformed tracers have been implemented in NorESM2, namely preformed dissolved oxygen (O_2^{pre}), phosphate (PO_4^{pre}), alkalinity (ALK^{pre}), and dissolved inorganic carbon (DIC^{pre}). They are initialized to zero at the beginning of the spin-up. During the model integration, in the bulk mixed layer of the model (i.e., the top 2 levels), the preformed tracers are set to the respective total, non-preformed values at each time step. Below the mixed layer, the preformed tracers are advected as passive tracers by the physical processes and hence are a measure of transport-induced (e.g., circulation, ventilation, etc.) changes. The preformed tracers are included for diagnostic purposes, such as identifying the sources of model-data misfits (Duteil et al., 2012). The preformed oxygen can be used to quantify the total and apparent oxygen utilizations (TOU and AOU) as well as O_2 disequilibrium (ΔO_2) in the interior ocean (Eqs. 10-11; Ito et al., 2004):

$$TOU = O_2^{pre} - O_2, \tag{10}$$

and

$$\Delta O_2 = TOU - AOU = O_2^{pre} - O_2^{sat}. \tag{11}$$

Here, the saturated oxygen (O_2^{sat}) is determined as a function of temperature and salinity (Garcia and Gordon, 1992). Due to its closed coupling with ocean circulation, the preformed oxygen can be used to separate biologically- from physically-induced

5   biases in the simulated interior biogeochemical tracers.

Following Bernardello et al. (2014), PO_4^{pre} is used to quantify the organic (soft tissue, DIC^{soft}), whereas both PO_4^{pre} and ALK^{pre} are used to quantify the inorganic (carbonate, DIC^{carb}), biologically-mediated carbon pump (Eqs. 12-14). We use a stoichiometry ratio of $P : N : C = 1 : 16 : 122$ in the model, such that DIC^{soft} represents remineralized particulate and dissolved organic materials and DIC^{carb} dissolution of particulate calcium carbonate in the water column:

10   $$DIC^{tot} = DIC^{pre} + DIC^{soft} + DIC^{carb}, \tag{12}$$

$$DIC^{soft} = r_{C:P}(PO_4^{tot} - PO_4^{pre}), \tag{13}$$

and

$$DIC^{carb} = 0.5 \cdot [ALK^{tot} - ALK^{pre} + (r_{N:P} + 1) \cdot (PO_4^{tot} - PO_4^{pre})]. \tag{14}$$

15   Equation 14 is slightly different from that of Bernardello et al. (2014), i.e., it uses the term $r_{N:P} + 1$ instead of $r_{N:P}$ because, in our updated code, we do not neglect the contribution of phosphate to alkalinity changes during biological production and remineralization. For instance, both nitrate and phosphate produced during organic remineralization increase the concentration of proton and therefore reduce the alkalinity (see also Section 3.1.3 of Paulmier et al., 2009).

The difference between total DIC and biologically altered DIC ($DIC^{soft}+DIC^{carb}$, or the biological carbon pump) therefore
20   represents the physical carbon pump (DIC^{pre}), which comprises saturated and disequilibrium components (Eq. 15). Here, a tracer of saturated DIC (DIC^{sat}) has been implemented. It is computed at the surface layer as a function of atmospheric pCO_2, total alkalinity, SSS, and SST. Below the first layer, DIC^{sat} is treated as a passive tracer advected by the circulation. Since the equilibration time-scale of the air-sea CO_2 fluxes is typically longer than the surface watermasses' residence time (e.g., in the deep water formation regions), a disequilibrium term (DIC^{diss}) is computed by subtracting the saturated from the preformed
25   DIC components. The DIC disequilibrium component is used to diagnose the importance of ventilation variability on the physical solubility pump, and to the overall DIC storage (Eggleston and Galbraith, 2018):

$$DIC^{pre} = DIC^{sat} + DIC^{diss}. \tag{15}$$

3.2   Natural inorganic carbon tracers

In order to comply with the Ocean Model Intercomparison Project (OMIP) of CMIP6 (Orr et al., 2017), we have implemented
30   a natural tracer of DIC (DIC^{nat}), which is formulated in the same manner as DIC^{tot}, except that the air-sea gas exchange is

computed with a fixed preindustrial atmospheric CO_2 concentration of 284.32 ppm. In a transient simulation with increasing atmospheric CO_2 concentrations, the difference between DIC^{tot} and DIC^{nat} represents anthropogenic DIC (DIC^{ant}):

$$DIC^{ant} = DIC^{tot} - DIC^{nat}. \tag{16}$$

The inclusion of a DIC^{nat} tracer also requires the implementation of respective 'natural' components for both the alkalinity and the particulate inorganic carbon ($CaCO_3$) tracers. This is because the anthropogenic CO_2 uptake alters the carbonate system and therefore the dissolution of $CaCO_3$. We note that anthropogenic carbon does not influence the biological production (e.g., nutrient concentrations and phytoplankton growth rate) in our model. Similarly, a 'natural' air-sea CO_2 flux has been added to the model output. These 'natural' tracers are only activated in simulations with atmospheric CO_2 that departs from the preindustrial value. Here, DIC^{nat}, $TALK^{nat}$, and $CaCO_3^{nat}$ are initialized in the same manner as DIC, $TALK$, and $CaCO_3$, respectively. In transient historical and future scenario simulations, these tracers provide insight into the natural carbon evolution under anthropogenic climate change.

In addition, DIC^{nat} also provides a more precise estimate of DIC^{ant} entering the ocean since the preindustrial period than simply taking the difference between DIC^{tot} at a specific time and its preindustrial mean value. Alternatively, these 'natural' tracers could be computed with a parallel transient simulation but with fixed preindustrial atmospheric CO_2 as the ocean carbon cycle boundary condition. The inclusion of natural tracers provides substantial saving of computational time, especially for high-resolution simulations. We note that the DIC^{nat} tracer has not been implemented in the sediment module. Hence, in very long time-scale transient simulations where the sediment changes become substantial, the DIC^{nat} tracer may include some uncertainties.

3.3 Carbon isotopes

The ^{13}C, and ^{14}C carbon isotope tracers have now been implemented in NorESM2. Naturally occurring stable carbon isotopes (^{12}C, ^{13}C, and ^{14}C) and their relative abundances provide valuable information about both past and present climate. Changes in the $^{13}C/^{12}C$ ratio are used, e.g., to (i) study glacial-interglacial atmospheric CO_2 changes from ice core air samples (Broecker and McGee, 2013; Bauska et al., 2016), (ii) reconstruct bottom water oxygen concentrations (Hoogakker et al., 2015), (iii) reconstruct paleo deep water circulation (Toggweiler, 1999; Curry and Oppo, 2005; Crucifix, 2005), (iv) investigate oceanic anthropogenic CO_2 uptake involving the Suess effect (Gruber and Keeling, 2001; Quay et al., 2003; Holden et al., 2013), and (v) evaluate model sensitivity and performance (Braconnot et al., 2012; Schmittner et al., 2013). The $^{14}C:^{12}C$ ratio is used as a circulation and age tracer (e.g., Skinner et al., 2017). Globally, the $^{12}C:^{13}C:^{14}C$ isotope ratio is about $99:1:10e^{-12}$. In order to allow comparison between different carbon isotope studies, the $^{13}C:^{12}C$ ratio is standardized and expressed in permil as $\delta^{13}C$ (Eq. 24 for DIC) (Zeebe and Wolf-Gladrow, 2001). Our implementation of ^{13}C follows the OMIP guidelines (Orr et al., 2017). The ^{14}C is standardized as $\Delta^{14}C$ (see Section 3.3.3). Variations in $\delta^{13}C$ are due to isotopic fractionation processes during air-sea gas exchange, photosynthesis and $CaCO_3$ formation, but the latter is neglected in our implementation (see also Section 3.3.2). For ^{14}C, each fractionation factor is the quadratic of the respective ^{13}C value (i.e., $\kappa^{14}C = \kappa^{13}C^2$). Lastly, ^{14}C is radioactive

and decays with a half-life of 5730 years to ^{14}N following:

$$dX^{14}C/dt = -\lambda \cdot X^{14}C, \tag{17}$$

where

$$\lambda[day^{-1}] = ln(2)/(5730 \cdot 365). \tag{18}$$

X represents any ^{14}C state variable. In the model, all ^{14}C tracers are normalized to prevent numerical errors from carrying values close to the precision of the model.

The newly implemented marine carbon isotope code parallels the respective total DIC code, and in addition includes fractionation during photosynthesis and air-sea gas exchange (as well as decay for the ^{14}C tracers). In addition to the dissolved inorganic tracers, the following ^{13}C and ^{14}C state variables have also been implemented: dissolved organic carbon, particulate organic carbon, calcium carbonate, phytoplankton, and zooplankton. Therefore, 12 new tracers are added (isotopic DOC, POC, CaCO$_3$, zooplankton, and phytoplankton). Due to the long equilibration time, the isotopic tracers are only activated in the computationally efficient configurations, such as the ocean carbon cycle stand-alone configuration (NorESM2-OC) or the low resolution version of the coupled model. Equilibrium times of the carbon isotopes are long due to the slow air-sea gas equilibration (Broecker and Peng, 1974) and long-term transient effects from the balance between sediment burial and weathering (Roth et al., 2014). Realistic equilibration times are therefore currently only obtained when bypassing the sediment module of the model when running the carbon isotopes, as well as omitting carbon isotope input from rivers. When bypassing the sediment, mass balance is maintained by redistributing POC fluxes to the sediment over the entire overlying water column, and by dissolving inorganic carbon fluxes as well as opal fluxes at the bottom of the model immediately. Ongoing work will add the possibility for a fast sediment spin-up for use in future versions of the biogeochemical ocean model. Since $\Delta^{14}C$ is governed mainly by radioactive decay and circulation, we focus on $\delta^{13}C$ in our description of isotopic fractionation effects (Sect. 3.3.1 and 3.3.2).

3.3.1 Air-sea gas exchange fractionation

During air-sea gas exchange, the lighter ^{12}C isotope preferentially escapes to the atmosphere. This fractionation process increases $\delta^{13}C$ of surface ocean DIC, although the local net effect depends on the interplay between the local thermodynamic air-sea disequilibrium, the air-sea gas exchange rate, and the strength of the fractionation (Schmittner et al., 2013; Morée et al., 2018). The air-sea fractionation is a function of temperature ($T[^{\circ}C]$) and CO$_3^{2-}$ fraction (fCO_3), such that fractionation increases with decreasing temperatures, resulting in higher $\delta^{13}C$ in colder than in warmer surface water (Zhang et al., 1995). The fractionation during air-sea gas exchange, which varies between ∼8 and 10.5 ‰, is due to the combined effects of (1) the fractionation between CO$_2$ and the different carbon species, α_{CT_g}, (2) kinetic fractionation, α_k, and (3) fractionation during gas dissolution, α_{aq_g}. The net air-sea $^{13}CO_2$ flux is formulated as follows:

$$F^{13}CO_2 = k_w \cdot \alpha_k \cdot \alpha_{aq_g} \cdot (p^{13}CO_2^{atm} - p^{13}CO_2^{sw}/\alpha_{CT_g}). \tag{19}$$

Any fractionation α_i in Eq. 19 can be expressed as $\alpha_i = (\varepsilon_i/1000+1)\%_{oo}$, where

$$\varepsilon_k = -0.88, \tag{20}$$

$$\varepsilon_{aq_g} = 0.0049 \cdot T - 1.31, \tag{21}$$

and

$$\varepsilon_{CT_g} = 0.0144 \cdot T \cdot fCO_3 - 0.107 \cdot T + 10.53. \tag{22}$$

In Eq. 19, k_w represents the gas transfer velocity for CO_2 according to Wanninkhof (2014) and T is in degrees C.

3.3.2 Biological fractionation

Phytoplankton prefers the lighter (^{12}C) isotope during photosynthesis, thereby increasing $\delta^{13}C$ of DIC in the surface ocean and producing low-$\delta^{13}C$ POC. In the interior ocean, the low-$\delta^{13}C$ POC is released back into the water column during remineralization/respiration, though without fractionation (Laws et al., 1995; Sonnerup and Quay, 2012). The 'biological isotope pump' thus creates a gradient of higher surface water $\delta^{13}C$ and lower deep water $\delta^{13}C$. The average fractionation during photosynthesis is approximately 19 $\%_{oo}$ (Lynch-Stieglitz et al., 1995; Tagliabue and Bopp, 2008). Even though many relationships for biogenic isotope fractionation have been proposed (e.g., Rau et al., 1996; Keller and Morel, 1999; Popp et al., 1998), the modelled $\delta^{13}C$ distributions are not very sensitive to the different parameterizations, especially not in the surface ocean (Schmittner et al., 2013; Jahn et al., 2015). In addition, some relationships may be unsuitable for global scale modelling applications due to the dependency on unknown parameters (e.g., specific species, cell size, and cell membrane permeability).

A parameterization by Laws et al. (1997) is chosen in NorESM2, where the biological fractionation ε_{bio} depends on the ratio between phytoplankton growth rate μ [day^{-1}] at every model time step and the aqueous CO_2^* concentration [$\mu molkg^{-1}$]:

$$\varepsilon_{bio} = \frac{6.03 + 5.5\mu/CO_2^*}{0.225 + \mu/CO_2^*}. \tag{23}$$

The growth rate μ is the brutto growth rate, uncorrected for losses such as mortality and exudation. ε_{bio} increases with increasing CO_2^* and decreasing μ. Fractionation values are kept within a realistic range of 5-26 $\%_{oo}$ to correct for the influence of μ/CO_2^* extremes (similarly as done by Tagliabue and Bopp, 2008). This nonlinear parameterization of Laws et al. (1997) as described in Eq. 23 is preferable over the linear formulation by Laws et al. (1995), because the linear formulation could result in unrealistic fractionation at high growth rates. Isotope equilibrium fractionation during $CaCO_3$ formation increases $\delta^{13}C$ of $CaCO_3$ and therefore depletes seawater of ^{13}C (thereby lowering seawater $\delta^{13}C$). Nevertheless, the fractionation effect during $CaCO_3$ formation is relatively small (i.e., in the order of -2 to +3 $\%_{oo}$, depending on species and environmental conditions; Grossman and Ku, 1986; Ziveri et al., 2003; Zeebe and Wolf-Gladrow, 2001) compared to the effects of air-sea gas exchange and photosynthesis. Therefore, fractionation during $CaCO_3$ formation is commonly omitted in modelling studies (e.g., Lynch-Stieglitz et al., 1995; Schmittner et al., 2013). There are additional uncertainties related to temperature- and

species-dependencies (Grossman and Ku, 1986; Zeebe and Wolf-Gladrow, 2001). Taking this into consideration, we have chosen not to implement fractionation during $CaCO_3$ formation in NorESM2.

3.3.3 Diagnostic and initialization

In order to evaluate the carbon isotopes against observations, we compute the diagnostic variables δ^{13}C and δ^{14}C according to their standard formulations, as follows:

$$\delta^{13}C = \left[\frac{DI^{13}C/DI^{12}C}{(^{13}C/^{12}C)_{PDB}} - 1 \right] \cdot 1000\text{\textperthousand}, \tag{24}$$

$$\delta^{14}C = \left[\frac{DI^{14}C/DIC}{NBS_{std}} - 1 \right] \cdot 1000\text{\textperthousand}, \tag{25}$$

and

$$\Delta^{14}C = \delta^{14}C - 2 \cdot (\delta^{13}C + 25) \cdot (1 + \delta^{14}C/1000), \tag{26}$$

where $(^{13}C/^{12}C)_{PDB}$ is the established Pee Dee Belemnite standard ratio of 0.0112372, and NBS_{std} is $1.170e^{-12}$ (Orr et al., 2017). The $DI^{12}C$ is computed as the difference between total DIC and $DI^{13}C$.

In the model, the initialization of the carbon isotope tracers is done as follows: first, the model is spun up with preindustrial boundary conditions until the non-isotope carbon chemistry reaches a quasi-equilibrium state. Next, we compute $DI^{13}C$ initial values by solving Eq. 24 for ^{13}C using the simulated AOU and DIC together with the δ^{13}C:AOU relationship reported by Eide et al. (2017), i.e., δ^{13}C=-0.0075·AOU+1.72. The $DI^{14}C$ is initialized by first calculating δ^{14}C by solving Eq. 26 using pre-industrial δ^{13}C from Eide et al. (2017) (with the missing upper 200 m copied from the 200 m depth values) and the observational-based estimate of pre-industrial Δ^{14}C (Key et al., 2004). This δ^{14}C is then converted to absolute model $DI^{14}C$ using Eq. 25. The remaining isotope tracers are initialized as $C \cdot R \cdot \zeta$, with C as the total carbon counterpart of the respective isotope tracer, R as $DI^{13}C/DI^{12}C$ or $DI^{14}C/DI^{12}C$ ratio, and $\zeta = 0.98$, a typical value for biological fractionation (applied to organic carbon components only).

Here, the prognostic atmospheric pCO_2 was initialized at 278 ppm from the start of the simulation. At initialization of the carbon isotopes, atmospheric $\delta^{13}C$ and $\Delta^{14}C$ are set to -6.5 ‰ and 0 ‰, respectively. Lastly, the results are presented as calibrated $\Delta^{14}C$ to account for long-term drift. That is, $DI^{14}C$ is multiplied with a factor F before standardization to $DI^{14}C$ corresponding to an atmospheric $\Delta^{14}C$ of zero permil ($^{14}C_{atmzero}$).

$$F = \frac{^{14}C_{atmzero}}{^{14}C_{atm}}, \tag{27}$$

where $^{14}C_{atm}$ in our simulation is found from the pre-calibrated $\Delta^{14}C_{atm}$ of approximately 36 ‰ and $^{14}C_{atmzero}$ is likewise determined by solving Eqs. 25 and 26 for $\Delta^{14}C=0$ ‰ in both cases using model $\delta^{13}C_{atm}$ (-7.5 ‰) and atmospheric pCO$_2$ (294 ppm). This leads to F=~2.5%.

4 Model simulations

Due to the long time scale of the large-scale ocean thermohaline circulation (flushing time is in the order of 1000-1500 years), a sufficiently long model integration in the order of at least 1000 years is required to achieve a quasi-equilibrium biogeochemical state in the interior ocean (Séférian et al., 2016). Prior to running any transient simulations, we have spun the model up for 1200 model years in a fully coupled configuration so that the ocean biogeochemistry reaches a quasi equilibrium state. In the spin-up simulation, all boundary conditions are fixed to constant preindustrial values, following the CMIP6 protocols (Eyring et al., 2016a). Due to the oceanic DMS fluxes, there is an internal feedback between the ocean biogeochemistry and the atmospheric radiative forcing during the spin-up. The end of the model spin-up is used as a starting point for (1) preindustrial control simulation (*piControl*, years 1850-2349), (2) transient *historical* simulation (years 1850-2014), and (3) *esm-piControl-spinup* simulation (100 model years). The end of simulation (3) is furthermore used as a starting point for (3a) an *esm-piControl* simulation (for 250 years), and (3b) a transient *esm-hist* (years 1850-2014) simulation. The use of '*esm-*' (i.e., in experiments 3, 3a, and 3b) follows the CMIP6 naming convention (Eyring et al., 2016a), which indicates emission-driven simulation where the atmospheric CO_2 is prognostically computed from ocean-atmosphere and land-atmosphere CO_2-fluxes, as well as from prescribed anthropogenic emissions (for *esm-hist*). Here, the atmospheric CO_2 is transported by the atmospheric circulation model. In the *esm-piControl-spinup* the atmospheric CO_2 concentration is relatively stable with a small drift of -0.002 ppm yr^{-1} and a long-term mean of 280.6±0.4 ppm.

Except for the carbon isotopes (see next paragraph), all analyses shown in this paper were extracted from the two transient historical simulations (prescribed CO_2-*historical* and prognostic CO_2-*esm-hist*). Since both simulations produce nearly identical climatology states, we only present results from the prescribed CO_2-*historical* simulation.

For the newly implemented carbon isotopes, a considerably longer spin-up is required. Therefore, the carbon isotope tracers were not activated in our fully coupled simulations. Instead, simulations with carbon isotopes switched on have been performed using the ocean carbon cycle stand-alone configuration of NorESM2. Additionally, a lower resolution ocean grid (using a similar tripolar grid as described above but with a nominally 2° resolution) has been used. This configuration avoids the high computational cost of running a long spin-up in a fully coupled configuration. The atmospheric forcing of the spin-up is the CORE normal year forcing (Large and Yeager, 2004), which represents a climatological mean year with a smooth transition between end and start of the year. Atmospheric CO_2, $^{13}CO_2$, and $^{14}CO_2$ concentrations are kept track of with a box-atmosphere (i.e., assuming 100% instant mixing), which is updated each time-step according to the modelled air-sea CO_2 fluxes using a conversion factor of 2.13 ppm Pg C^{-1}). These simplified prognostic atmospheric fields are simulated from the start of the spin-up (and the subsequent start of the carbon isotope simulation). As mentioned above, we have not implemented the carbon isotopes in the sediment compartment of the model. Therefore, the sediment module of HAMOCC was switched off for the carbon isotope simulations presented here. Otherwise, the setup of the ocean carbon cycle stand-alone configuration is as described in Schwinger et al. (2016). The model spin-up was run for 5000 years, of which the first 1000 years were run without carbon isotopes. At year 1000 (4000), after the largest transient changes in biogeochemical tracers have flattened out, we initialised the ^{13}C (^{14}C) tracers as described above. At the end of year 5000, the model reaches a quasi-equilibrium state,

which approximately corresponds to the preindustrial state. Here, we evaluate the simulated carbon isotope simulations against the preindustrial estimates of the respective tracers.

5 Results

Here, we evaluate the model performance in simulating the mean climatological state of key biogeochemical tracers as well as the evolution of air-sea CO_2 fluxes from the transient *historical* and *esm-hist* simulations. The carbon isotope results are from a stand-alone ocean simulation.

5.1 Statistical performance summary

We assess, relative to the observational estimates and the earlier version NorESM1, the simulated long-term annual mean of global hydrography and biogeochemical tracer distributions. Where relevant, the mean seasonal cycles are also evaluated for the surface values. The list of parameters, the averaging periods, and the respective observational data used to assess the model performance are given in Table 2. We use spatial correlation and normalized-RMSE (root mean squared error) metrics to measure the model-data difference and determine whether or not the current model version has improved and performed better than the earlier version. The normalization was done by dividing the RMSE with the standard deviation of the respective observations.

Figure 2b shows that, except for the surface layer, the normalized-RMSE of most of the NorESM2 variables' mean climatology is either noticeably improved or relatively similar to that of NorESM1. At 500 m depth, all variables but salinity have lower RMSE values. For many of the biogeochemical tracers (phosphate, nitrate, oxygen, and DIC), NorESM2 shows better agreement with data throughout the water column. Similarly, the respective spatial correlations with the observations are considerably improved for most variables, especially for nitrate, DIC, and alkalinity (Fig. 2a). For surface seasonality, NorESM2 performs fairly comparable to NorESM1, with improvements in all seasonal metrics (NRMSE and spatial pattern) for surface salinity and net primary production. NorESM2 simulates slightly larger NRMSE in its surface nutrients (phosphate, nitrate, and silicate) in both their annual and seasonal average values relative to NorESM1. This is attributed to the anomalously high concentration in the Arctic Ocean and parts of the Southern Ocean (just north of the Antarctic Circumpolar Current). More details on the performance of each specific variable are discussed in the following subsections.

5.2 Temperature

NorESM2 simulates a warm bias for both preindustrial conditions and the contemporary surface ocean (Fig. 3d), where a warm bias as high as 5°C is simulated in some regions of the Southern Ocean. Cold biases are simulated in parts of the north and equatorial Pacific, North Atlantic subpolar gyre, and the Arctic Ocean. The climatological mean temperatures are broadly similar between both NorESM versions with NorESM2 having less spatial correlations at 1 and 1.5 km depths (Fig. 2a,b). At depths below 2 km, with the exception of North Pacific, NorESM2 simulates less biases (Fig. 3e,f,h,i). This improvement is related to the more accurately simulated Antarctic Bottom Water (AABW; see also Supplemental Fig. S1) in both the Pacific

and Atlantic basins, as also depicted in Fig. 3. While NorESM1 simulates a too strong AMOC strength (roughly 31 Sv at 26°N), NorESM2 has a more reasonable strength of approximately 21 Sv. Nevertheless, the warm bias of 1-2°C in the North Atlantic Deep Water (NADW) remains when compared to observations. The cold bias seen previously in the intermediate watermass in the Southern Ocean and North Pacific has been improved in the new version. In the Atlantic sector just south of 30°N at 1 km depth, there is a warm bias of up to 5°C (Fig. 3e), which could be related to the anomalously strong overflow watermass from the Mediterranean Sea. Nevertheless, the cold bias in the Atlantic and Pacific tropical/subtropical thermocline simulated in NorESM1 is now improved in NorESM2. Temperature values from NorESM2-LM are shown in Supplemental Fig. S2.

5.3 Salinity

The RMSE in surface salinity is reduced in NorESM2, mostly owing to improvements in the Arctic, where the previous model version simulates too saline water (Fig. 4d,g). Also at the surface, NorESM2 simulates anomalously too fresh and too saline biases in the Pacific and the Atlantic basins, respectively. In the subtropical south Pacific, the negative bias is as high as -2 psu, and is consistent with a too strong precipitation rate in this region simulated by the atmospheric component (not shown). Positive biases are simulated in the northern Indian Ocean, and along the Benguela current extension. In the interior, the salinity bias in the Pacific and the Atlantic is in the order of ±0.11 and +0.4 psu, respectively (Fig. 4e,f). In the NADW, NorESM2 displays a positive bias, which is, however, smaller than that of NorESM1 (Fig. 4h; bias greater than 0.5 psu). Similar to temperature bias, NorESM2 produces too much saline water around 30°N at 1 km depth in the Atlantic (Fig. 4e), due to overflow of high salinity Mediterranean watermasses. In the interior Pacific and Southern Ocean, both models' performances are generally comparable (Fig. 4e,f,h,i). Except for the surface salinity, simulation with lower atmospheric resolution (NorESM2-LM) depicts similar salinity pattern throughout the water column (Supplemental Fig. S3).

5.4 Mixed layer depth

Seasonally-averaged mixed layer depth (MLD) from NorESM2 and observations are shown in Fig. 5. To be consistent with the observational estimates (de Boyer Montégut et al., 2004), we have computed our MLD using the σ_T (density) criteria, which is the first depth where the change from surface σ_T of 0.03 has occurred. In NorESM1, the MLD is generally too deep throughout most ocean regions. The new improvements in the MLD parameterization in NorESM2 reduce this bias considerably, especially in the low- and mid-latitude and the North Pacific regions. In the subpolar North Atlantic and parts of the Southern Ocean, the simulated MLD is still deeper than the observation-based estimates. In the Weddell Sea, NorESM2 also persistently simulates a deep MLD throughout the year, a feature not seen in the observations. There is no significant difference between MLD simulated in NorESM2-MM and NorESM2-LM (Supplemental Fig. S4).

5.5 Ocean ventilation

To assess the simulated ventilation, we compare the passive chlorofluorocarbon (CFC-11) tracer distribution in the interior Atlantic and Pacific Oceans as simulated by NorESM2 with that from observations, as shown in Fig. 6. We compare the

simulated CFC-11 from calendar year 2000 with climatological estimates of Key et al. (2004). Similar to the observations, high values of CFC-11 are generally simulated in the upper 1 km in both the Atlantic and the Pacific, with the exception of the North Atlantic, where up to 0.5 nmol CFC-11 m^{-3} penetrates down to 5 km depth. In the mid-latitude North Atlantic (i.e., 30°N), the model is unable to simulate the observed high values at around 1 km depth. This is likely due to the discrepancy in the watermass origin between the model and observations. Here, the watermass in the model is too old, as also seen in the too high Apparent Oxygen Utilization and dissolved inorganic carbon (see below subsections on oxygen and DIC). The model simulates too strong deep water ventilation in both the Atlantic and Pacific sectors of the Southern Ocean as well as in the high latitudes of the North Atlantic. Similar ventilation patterns are also produced by NorESM2-LM (Supplemental Fig. S5), with slightly less ventilated North Atlantic.

5.6 Nutrients

In general, the climatological nutrient distributions (phosphate, nitrate, and silicate) in NorESM2 are either comparable or improved compared to those of NorESM1, both in spatial correlation and normalized RMSE (Fig. 2a,b). At depth, these improvements are due to the new particulate organic carbon sinking scheme, where the sinking velocity increases linearly with depth. In NorESM1, the sinking speed is constant with depth, leading to more organic material being remineralized in the upper 1.5 km. The sinking scheme in NorESM1 produces anomalously high regenerated phosphate at intermediate depth (approximately between 100 and 1500 m depth; Fig. 7h,i). A consequence of this is a too strong oxygen minimum zone (OMZ; see also next subsection) and denitrification in the low latitudes, where the nitrate concentration becomes overly depleted. On the other hand, at depths greater than 1500 m, NorESM1 exhibits too low concentrations of all nutrients relative to the observations (panels (h) and (i) of Figs. 7-9).

With the new sinking scheme, more organic material reaches the deep ocean and gets remineralized there. As a result, model data biases in phosphate and nitrate in the interior are noticeable improved (Figs. 2b, 7e,f, 8e,f). In the Pacific OMZ, a reduced export production in NorESM2 also contributes to the reduced nutrient bias. In the interior North Atlantic, despite strong positive spatial correlation with the observations, NorESM2 shows a positive bias at depth below 3000 m and north of 30°S (Figs. 7e, 8e, 9e). Through analyzing the quasi-conservative 'PO' tracer (Broecker, 1974), we are able to attribute this to the bias in the simulated watermass (Supplemental Fig. S1). In NorESM2, this region is dominated by Antarctic Bottom Water, whilst the observations indicate NADW as the main watermass. As with NorESM1, the current model still simulates too low nutrient concentrations in the North Pacific intermediate watermass (Figs. 7f, 8f, 9f). This is likely associated with the too low surface primary production simulated in this region (see also Section 5.8), leading to limited organic matter available for remineralization at depth. We note that the circulation bias in this region could also contribute to the nutrient bias. In the Southern Ocean, too strong ventilation potentially leads to the negative nutrient biases in both Atlantic and Pacific sectors.

In NorESM2, less export production and deeper distribution of POC through the changed sinking scheme lead to a reduced rate of denitrification in the Pacific oxygen minimum zone and a greatly improved nitrate distribution (Fig. 8f). In NorESM1, far too much nitrate was consumed for denitrification (Fig. 8i). The silicate spatial distribution in NorESM2 closely resembles the phosphate distribution (Figs. 9a-c and 7a-c), with similar biases across the vertical sections of Atlantic and Pacific (Figs.

9e,f and 7e,f). At high-latitudes, NorESM2 overestimates the surface silicate concentration (Fig. 9d), which could be attributed to the reduced opal export sinking speed relative to our earlier model version (30 instead of previously 60 m day^{-1}).

In NorESM, the bulk phytoplankton growth rate is limited by multiple nutrients (i.e., phosphate, nitrate, and dissolved iron), in addition to temperature and light (see also Section 2.3.2 of Schwinger et al., 2016). The model does not explicitly simulate

5   diatom and calcifier classes.The inclusion of iron is critical to simulate the observed HNLC (High Nutrients Low Chlorophyll) regions in the world ocean where year-long elevated concentrations of both nitrate and phosphate are not exhausted by phytoplankton (de Baar et al., 1995; Martin and Fitzwater, 1988). The three major HNLC regions are the subarctic North Pacific, the eastern and central equatorial Pacific, and the Southern Ocean. Here, low levels of bio-available iron concentrations limit the phytoplankton growths. In NorESM1, only the subarctic North Pacific is simulated to be iron-limited, with the other two

10   HNLC regions being mostly limited by nitrate, as shown in Fig. 10. Iron limitation is also incorrectly simulated in parts of the subtropical North Pacific, South Pacific, and most parts of the western Pacific. Following improvements in the iron parameterization, the three HNLC regions are now shown to be iron-limited in NorESM2. Nevertheless, the iron limitation bias in the western equatorial Pacific remains.

5.7   Dissolved oxygen

15   At surface level, dissolved oxygen is mostly constrained by solubility and hence sea surface temperature. Both NorESM1 and NorESM2 perform similarly for dissolved oxygen at the surface with subtle improvements in the seasonal spatial correlation coefficient of NorESM2 (Fig. 2a,c). As with nutrients, the climatological distributions of interior oxygen improved considerably when compared to NorESM1 (Fig. 11), which is one of the CMIP5 ESMs with too strong OMZ (Cabré et al., 2015). In NorESM2, the OMZ volume is reduced considerably in both the equatorial Atlantic and Pacific, and the absolute dissolved

20   oxygen values are also much improved (Fig. 11e,f). Here the remaining bias is related to the nutrient trapping issue (Six and Maier-Reimer, 1996), as can also be seen from too high apparent oxygen utilization (AOU; Fig. 12d). In the interior Pacific and Atlantic roughly at 2 km and deeper, NorESM2 simulates considerably higher oxygen concentration than the observations by as much as 50% (North Pacific deep water; Fig. 11f). In the North Pacific deep water, this is primarily due to the still too little organic matter flux reaching below the mesopelagic zone, leading to too low apparent oxygen utilization (Fig. 12d). The

25   uncertainty in the dissolved organic carbon (not shown), which is currently not well constrained due to lack of observational data, could also play a role in this. In addition to biological constraints, the remaining interior oxygen bias can be attributed to the too strong Antarctic Bottom Water (AABW) ventilation, which carries a colder (Fig. 3e,f) and higher oxygen saturated watermass into both the Atlantic and Pacific bottom waters (Fig. 11e,f).

5.8   Biological production

30   In NorESM1, the primary production is generally too strong in the equatorial Pacific and at high latitudes during summer months. In the subtropical oceans, the simulated production is too low relative to the observational estimates. With the newly tuned ecosystem parameters of NorESM2, the spatial productivity patterns are improved considerably with an average absolute bias in the open ocean of less than 5 mol C m^{-2} yr^{-1} (Fig. 13a). In NorESM1 these biases reach more than 10 mol C m^{-2}

yr^{-1}, especially in the Equatorial Pacific, the South Atlantic and the Southern Ocean. Seasonally, the spatial patterns are also improved when compared to the observations with a correlation of approximately $r = 0.5$ (Figs. 2c, 13c). The RMSE has also reduced considerably, particularly in the October-November-December months, where NorESM1 simulates a much too strong spring bloom in parts of the Southern Ocean which is overestimated by as much as a factor of eight (e.g., Figs. 13e, 14e and

5   Nevison et al., 2015). Similarly, the spring blooms in the North Atlantic and North Pacific are overestimated in NorESM1 (Figs. 13e, 14a). The improved spring bloom characteristics at high latitudes, however, comes at the cost of a too low annual mean productivity in the North Atlantic and North Pacific.

     Due to unresolved physical dynamics, the model is still unable to reproduce the observed high productivity in coastal regions. Globally, the contemporary total primary production in NorESM2 (NorESM1) is 35.3 (39.9) Pg C yr^{-1}. These estimates are

10   lower than the observational (MODIS, excluding coastal areas) estimates of 46.1 Pg C yr^{-1} but within the broad range of CMIP5 models (Bopp et al., 2013). In our model, export production is estimated as the flux of particulate organic carbon exiting the base of the euphotic zone (here assumed to be 100 m depth), as a function of zooplankton and phytoplankton mortalities and zooplankton fecal materials. Table 3 shows that the export production in NorESM2 is 5.39 Pg C yr^{-1}, as compared to 7.90 Pg C yr^{-1} simulated by NorESM1. Current estimates of the global export production remain highly uncertain, from 5 to >12

15   Pg C yr^{-1}, with a more recent satellite-based approach that accounts for food-web processes revealing values of 6±1.2 Pg C yr^{-1} (Siegel et al., 2014).

     Table 3 also summarizes other export production metrics from both model versions. As a consequence of the new particle sinking scheme, there is more POC exported into the deep ocean. This is especially reflected by the values of transfer efficiency ($T_{eff-1km}$), which is calculated as a ratio between POC fluxes at a depth of 1000 m and of 100 m. The $T_{eff-1km}$ in NorESM2

20   (0.24) is increased by a factor of four relative to that in NorESM1 (0.06). Compared to a recent estimate of transfer efficiency reconstructed from observed interior biogeochemistry (Fig. 13b; Weber et al., 2016), NorESM2 still simulates too high transfer efficiencies of >50% in the eastern Equatorial Pacific (Fig. 13d). On the other hand, the transfer efficiency in the Southern Ocean and northern high latitudes are comparable with observations. This represents a significant improvement when compared to NorESM1 (Fig. 13d,f), which simulates nearly uniform $T_{eff-1km}$ values of less than 0.1 in all ocean regions with the

25   exception of eastern Equatorial Pacific and Equatorial Atlantic.

     Figure 14 shows the seasonal cycle of biological production rates as simulated by NorESM1 and NorESM2 averaged over different ocean regions together with observation-based estimates. The regional mean values in NorESM2 are generally lower than those in NorESM1, except in the North and tropical Pacific (Fig. 14b,c). Nevertheless, Fig. 2d shows that NorESM2 simulates a lower normalized RMSE than NorESM1 in all seasons. As stated above, this bias could be reduced even more

30   if we excluded the continental shelf regions. Nevertheless, Fig. 14 shows that the seasonal phase and amplitude of biological production rates in NorESM2 in the North Atlantic, North Pacific, and the southern hemisphere regions are closer to the observations when compared to NorESM1. In the southern hemisphere (south of 20°S), NorESM2 no longer produces the large summer bias seen in NorESM1.

5.9 DMS production and fluxes

In NorESM2, DMS production is tuned towards the climatological observations from Lana et al. (2011). Figure 15 shows the surface DMS concentration for each season together with the observation-based estimates. To first order, the DMS distribution follows the spatial pattern of the simulated primary production, with higher concentrations during spring/summer periods in high latitude regions. In the Equatorial Pacific and Atlantic upwelling regions, the model overestimates DMS concentrations. Similarly, in the North Pacific, where the model underestimates productivity during the boreal spring bloom (see also Fig. 14b), the DMS concentration is lower than observed (Fig. 15b,f).

The simulated DMS concentration in the North Atlantic is comparable with observations. In the Southern Ocean, the model produces the observed high concentrations during summer months (JFM) along the 40-45°S latitude band well Fig. 15e). In winter periods, the DMS concentration approaches zero in the model owing to the too low productivity, whilst the observations still indicate values of approximately 1 μmol S m^{-3}. For the present day period (1971-2000), the simulated global DMS flux is 19.76±0.19 Tg S yr^{-1}, which is at the lower end of observation-based estimates (17.6-34.4 Tg S yr^{-1}).

5.10 Dissolved inorganic carbon and alkalinity

Except for the polar Southern Ocean, the surface alkalinity concentrations in NorESM1 are approximately 100 μmol L^{-1} higher than the observational estimate. And since the spin-up was forced with constant preindustrial atmospheric CO_2 concentrations, the surface DIC concentration adjusted (also anomalously high bias; Figs. 16g and 17g) to yield the 'correct' surface pCO_2. Consequently, biases in surface DIC and alkalinity compensate one another to yield the approximately 'correct' carbonate ion concentration (i.e., alkalinity minus DIC), seawater CO_2 buffer capacity, and air-sea CO_2 fluxes.

In NorESM2, we alleviate the surface alkalinity bias by increasing the surface sink associated with calcium carbonate production. This is done by increasing the $CaCO_3$ to phosphate uptake ratio ($R_{CaCO_3:P}$ in Table 1). As a result, the export of particulate $CaCO_3$ increases from 0.49 Pg C yr^{-1} in NorESM1 to 0.66 Pg C yr^{-1}, with both estimates still within the range of the observation-based synthesis of 0.52±0.15 Pg C yr^{-1} (Dunne et al., 2007). This modification increases the PIC:POC export ratio to 0.13 (0.06 in NorESM1, see also Table 3) and considerably improves the surface DIC and alkalinity concentrations in NorESM2 (Figs. 16a,d and 17a,d). At the same time, the spatial correlations with observations are also improved as well as the normalized RMSE (see Fig. 2a,b). We note that in few regions, e.g., the subtropical South Pacific, the model still underestimates the observed DIC and alkalinity concentrations. We note that the PIC:POC ratio is still within the large range of other studies (0.03 to 0.25; Koeve, 2002; Sarmiento et al., 2002)

As at the surface, the spatial distributions and normalized bias of interior DIC and alkalinity in the NorESM2 improve considerably throughout the water column relative to NorESM1 (Fig. 2a,b). In both the interior Atlantic and Pacific basins, the spatial distribution and magnitude of DIC biases closely resembles that seen in the nutrients (e.g., phosphate; Figs. 16e,f, 7e,f), when multiplied by the constant stoichiometry in the model ($R_{C:P}$=122). This suggests that the mechanisms driving the nutrient bias are also responsible for the bias in interior DIC. For instance, the positive anomaly in the equatorial Pacific between 1 and 3 km depths originates from too much biological remineralization in the model.

The simulated interior alkalinity concentrations in NorESM2 between 1 and 3 km depths are anomalously high, which can partially be attributed to too low interior remineralization in the Atlantic (see also AOU values Fig. 12c) or too high $CaCO_3$ export production (Table 3).

5.11 Surface pCO_2 and sea-air CO_2 fluxes

The NorESM2 pCO_2 spatial correlation relative to the observations is improved in almost all seasons when compared to NorESM1, while the NRMSE is reduced for JFM and AMJ months (Fig. 2c,d). Within these months, improvements are mostly seen in the Southern Ocean, where too strong surface mixing in NorESM1 leads to anomalously high pCO_2. The climatological mean of contemporary surface pCO_2 in NorESM2 compares well with the observational compilations, as seen in Fig. 18a,e. Similar improvements are also seen in the CO_2 fluxes, where NorESM2 simulates the broad spatial patterns relatively well (Fig. 18c,g). NorESM2 also produces moderately weaker annual mean carbon flux in the northern mid- to high-latitudes than NorESM1. Figure 18f,h shows the zonally-averaged monthly surface pCO_2 and CO_2 fluxes in NorESM2. Here, the model also agrees well with the observation-based estimates (Fig. 18b,d) in term of amplitude and temporal variability, with distinct seasonal cycle between $20°$ and $45°$ south/north. In the extra-tropical oceans (between $45–65°N$ and south of $60°S$), the simulated winter (January-March and July-September in northern and southern hemispheres, respectively) pCO_2 is considerably lower than that seen in the observations. In these regions, nevertheless, the carbon sink during these periods is comparable with observations (Fig. 18d,h).

Figure 19 depicts the mean seasonal cycle of sea-air CO_2 fluxes from NorESM models and observations, averaged over different regions. In the North Atlantic, North Pacific, and the mid-latitude southern hemisphere (between $20–40°S$), the seasonal phase and mean integrated annual CO_2 fluxes in NorESM2 compare better with the observations than those in NorESM1 (Fig. 19a). Nevertheless, NorESM2 simulates a stronger than observed carbon sink in the Labrador Sea and along the Kuroshio current extension during boreal winter months. We note that the Landschützer et al. (2014) data estimates higher surface pCO_2 (hence a weaker carbon sink) in these regions than the observational estimates from Takahashi et al. (2009). Despite the warm SST bias in most of the tropics, NorESM2 simulates a moderately weaker than observed CO_2 outgassing throughout the year (red line as compared to blue line in Fig. 19c). A potential explanation for this is the weaker upwelling rates of DIC-rich deep watermasses in the model. In the Southern Ocean (south of $40°S$), strong bias in the seasonal amplitude in NorESM1 is considerably reduced (Fig. 19e,f), due to the improvements in the biological production in this region. Nevertheless, here the seasonal phase in NorESM2 is approximately reversed compared to observations: the strongest sink is simulated in the austral winter months whereas observational estimates indicate summer months.

5.12 Transient changes

In this subsection, we describe the global mean surface air temperature and oceanic carbon uptake over the historical period (1850–2014) as simulated by NorESM2. For this, we discuss the two transient simulations: (i) *historical* and (ii) *esm-hist*. Similar to SST (see Fig. 3), there is a warm-bias in the simulated surface air temperature. For the period of 1850-1859, the NorESM2 global mean surface air temperature is $14.5°C$ compared to $13.7°C$ from the HadCRUT4 dataset (Morice et al.,

2012). Nevertheless, the simulated warming between 2005-2014 and 1850-1859 is 0.7°C, comparable to that from observations of 0.8°C (Fig. 20a). The warming in *esm-hist* is lower, 0.6°C. Figure 20a also shows that NorESM2 (orange and green lines) simulates warming rates that are comparable to observations (blue line) between 1970 and 2010, but shows a stronger cooling between 1950 and 1970 (*historical* and *esm-hist*).

5   In both simulations, the global mean surface ocean pCO_2 follows the respective atmospheric CO_2 trend over the simulation periods. Towards the end of the historical period, the oceanic pCO_2 (solid green and orange lines) diverges from, i.e., is lower than, the atmospheric counterpart (dashed-green and -orange lines) by approximately 20 ppm (Fig. 20b). Consistent with the lower surface ocean (than the atmosphere) pCO_2, the ocean carbon uptake continues to increase over most of the transient period in both simulations (Fig. 20c). In the *historical* simulation, the carbon sink stabilizes at roughly 0.7 Pg C yr^{-1} between

10   1910 and 1960. This flattening of the uptake strength is associated with the slow down in the atmospheric CO_2 growth rate. Figure 20d confirms that the atmospheric growth rate weakens during this time window (orange bars in Fig. 20d). On the contrary, the carbon sink in *esm-hist* steadily increases during the same period, also consistent with the steady increase in the simulated prognostic atmospheric CO_2 (green-bars in Fig. 20d).

     From 1960 onward, the atmospheric CO_2 growth rates in both simulations increase almost linearly in time from 0.8 to more

15   than 2.0 ppm yr^{-1}. Consequently, the ocean carbon uptake strengths increase as well, from approximately 1 Pg C yr^{-1} in the 1960s up to 2.5 Pg C yr^{-1} in 2014 (in both *historical* and *esm-hist*). Rapid strengthening in ocean carbon uptake is also evident in estimates from the Global Carbon Project (GCP, blue line in Fig. 20; Le Quéré et al., 2018). For the 1980s and 1990s, the simulated carbon uptake is also well within the IPCC (Intergovernmental Panel for Climate Change, Denman et al., 2007) estimates (Table 4). In NorESM2, a new tracer *DIC^{nat}* has been implemented (see also Section 3.2), and it enables us to more

20   accurately estimate the anthropogenic carbon uptake and storage in the ocean. Using this tracer, we can also estimate the net flux of anthropogenic carbon into the ocean during the historical period, as depicted by the purple line in Fig. 20c). The strong resemblance between the orange and purple lines suggests that the long-term trend in oceanic carbon sinks is associated with the increasing atmospheric CO_2, rather than changes in climate states (as expected for the historical runs where the change in the climate state is relatively small). We note that, in the preindustrial control simulation, the ocean is a weak net carbon

25   sink, of approximately 0.1 Pg C yr^{-1}. Table 4 also shows that the cumulative carbon uptake by the ocean for 1850-1994 and 1994-2011 is well within the observation-based estimates. The cumulative carbon uptake in NorESM2 is lower than that of NorESM1 and compares better with observations.

5.13   Distribution of $\delta^{13}C$ and $\Delta^{14}C$

As stated above, the carbon isotopes tracers are not included in the coupled ESM configuration and only simulated in a

30   preindustrial stand-alone ocean configuration. We also note that although the stand-alone ocean simulation is not a direct representative of the coupled ESM simulation, its equilibrium ocean state is very comparable. For instance, the interior distribution of phosphate and DIC concentration in the stand-alone ocean simulation (Supplemental Figs. S6, S7) share very similar characteristics with that produced in the coupled configuration (Figs. 7a-c, 16a-c). At the end of preindustrial spin-up, Fig. 21a-c shows that the spatial pattern of $\delta^{13}C$ is in fair agreement with the gridded preindustrial observational estimate of Eide

et al. (2017). Nevertheless, the ocean component of NorESM2 simulates weaker variability than observed, i.e., it is unable to reproduce both very low (negative) and high (positive) values. Therefore, the simulated $\delta^{13}C$ concentrations in the relatively younger watermasses, such as the North Atlantic Deep Water (NADW) and the Antarctic Intermediate Water (AAIW), have negative bias relative to the observations (Fig. 21e). On the contrary, positive biases are depicted in the older Antarctic Bottom

5 Water (AABW) and in the deep North Pacific (Fig. 21e,f). The $\delta^{13}C$ can be decomposed into biological and residual (air-sea gas exchange and circulation) components (Broecker and Maier-Reimer, 1992; Eide et al., 2017):

$$\delta^{13}C = \delta^{13}C_{BIO} + \delta^{13}C_{AS}, \tag{28}$$

where $\delta^{13}C_{BIO}$ can be estimated as a function of phosphate and DIC distribution and their global mean values:

$$\delta^{13}C_{BIO} = \frac{-19 \cdot r_{C:P}(PO_4 - \overline{PO_4})}{\overline{DIC}} + \overline{\delta^{13}C}. \tag{29}$$

10 Applying this decomposition, we can attribute the majority of the differences between model and observational estimates of $\delta^{13}C$ to biases in the biological component (Fig. 22). The $\delta^{13}C_{BIO}$ reveals that in the Southern Ocean (south of $\sim$55°S), as well as in its exported deep waters, NorESM2-OC simulates too high $\delta^{13}C$ due to the too small regenerated signal in these waters. The negative $\delta^{13}C$ anomaly in the North Atlantic of about -0.5 ‰ is a combination of a too low $\delta^{13}C_{BIO}$ signature in NADW (Fig. 22e), combined with a too negative influence from air-sea gas exchange and circulation as compared to observational

15 estimates (the residual term $\delta^{13}C_{AS}$). In the Pacific the positive anomaly from the Southern Ocean persists throughout most of the basin due to too weak remineralization, except for at intermediate depths where remineralization is high (see also AOU, Fig. 12).

The simulated $\Delta^{14}C$ distribution is in general agreement with the pre-industrial observational estimate by Key et al. (2004). Nevertheless, interior model-observation biases are in the range of $\pm$50 ‰. Waters south of 60°S are positively biased as

20 compared to observations (Fig. 23), indicating too young and well-ventilated waters in this region. This positive bias of 20-50 ‰ is carried into the Atlantic and Pacific basins (Fig. 23e-f) and is equivalent to an underestimation of radiocarbon age by 200-400 years. North of the Equator, a negative bias of similar magnitude indicates too old water masses in the Atlantic basin below 3 km depth as well as throughout the water column in the northern half of the Pacific basin. The top 800m of the water column has a negative bias of 100 ‰, which we attribute to the too negative atmospheric $p^{14}CO_2$ before calibration (-36 ‰)

25 and biases in air-sea equilibration and fractionation. Calibrated $\Delta^{14}C_{atm}$ is by definition 0 ‰, $\delta^{13}C_{atm}$ equilibrates at -7.5 ‰, and atmospheric pCO_2 is 294 ppm at the end of the simulation.

6 Summary and discussion

The ocean biogeochemical component of the Norwegian Earth System Model (NorESM) has been updated from version 1 (as used in CMIP5) to version 2 (NorESM2). These developments focus on alleviating known biases in mean states and seasonal

30 cycles of key variables when compared to the observations. This paper describes new and improved processes, newly implemented diagnostic and carbon isotope tracers, and highlights the model improvements relative to the earlier model version.

On the biogeochemistry side, we have introduced a revision to the particulate organic carbon vertical sinking scheme, an improved tuning of ecosystem parameters, riverine inputs of nutrients and other biogeochemical constituents, an updated air-sea gas exchange parameterization, and atmospheric deposition of nitrogen. In NorESM2, the ocean biogeochemistry also simulates (i) fully interactive oceanic DMS fluxes coupled to the atmospheric model, (ii) newly implemented preformed tracers, which enable us to perform a more detailed diagnosis of physical and biogeochemical sources and sinks in future studies, and (iii) carbon isotopes that can be used e.g. in extended paleo time-scale simulations.

On the physical side, the simulated Atlantic Meridional Overturning Circulation strength is considerably improved. An hourly coupling (previously daily) across the ocean-atmosphere-ice interfaces has been implemented. Intensive fully coupled testing prompted further attempts to optimize mixed layer physics parameters, which slighly reduce the bias in MLD when compared to our earlier model version.

In connection to our contribution to the CMIP6 simulations, two model configurations have been prepared, NorESM2-LM and NorESM2-MM, where the latter adopts a higher atmospheric resolution. In both versions, the ocean components are identical. Following the CMIP6 protocols (Eyring et al., 2016a), we have performed preindustrial control (*piControl*, years 1850-2349) and transient climate (*historical*, years 1850-2014) simulations. Here, we analyzed the simulations performed using both model versions.

As a result of the above developments, the overall performance of NorESM2 in simulating the climatological state of interior ocean biogeochemistry has improved considerably. Some of the key improvements include (i) better representation of the equatorial Pacific OMZ, (ii) improved interior nutrient distributions, and (iii) representation of iron limitation in the Southern Ocean, the equatorial and North Pacific.

With respect to transient ocean carbon sinks, previous studies have indicated the importance of the background biogeochemical state, such as alkalinity, dissolved inorganic carbon, and buffer capacity, in order to adequately simulate the long-term trends (Hauck and Völker, 2015; Fassbender et al., 2018; Lebehot et al., 2019). NorESM1 exhibits a considerable bias for the background biogeochemical state, especially in surface alkalinity concentrations. These biases have been substantially reduced in NorESM2, resulting in a more adequate representation of the background buffer factor and improved model fidelity in simulating the temporal evolution of the ocean carbon sink.

The seasonality of upper ocean biogeochemistry has been identified as critical for quantifying a model's uncertainty in its long-term projections of oceanic carbon uptake (Fassbender et al., 2018). Further, with ongoing anthropogenic CO_2-emissions, the seasonal variability of regional sea-air CO_2-fluxes is expected to amplify. This amplification, which is linear for the thermal component and nonlinear for the biophysical component of oceanic pCO_2 (Fassbender et al., 2018), can also impact the long-term evolution of sea-air CO_2-fluxes. In this aspect, NorESM1 simulates a considerable bias in the seasonal cycle of biological production and air-sea CO_2 fluxes, particularly in the Southern Ocean. The updated set of ecosystem parameters in NorESM2 is able to mitigate these biases to some extent. In the North Atlantic, North Pacific, and most parts of the Southern Ocean, the seasonal cycle (both in phase and amplitude) of primary production and CO_2-fluxes in NorESM2 reflects observational estimates and their driving mechanisms more accurately (Landschützer et al., 2018). We note however that there is a mismatch between the CO_2-fluxes' seasonal cycle in observations and NorESM2 in the Southern Ocean between 40°N and 60 °N. A

closer attention to the associated physical (e.g., solubility) and biogeochemical (e.g., biological productivity) drivers in this region is needed when considering future scenarios in the future. However, general seasonal characteristics are improved and we are confident that NorESM2 will provide a better estimate of future changes.

Despite numerous model improvements, several biases remain in the updated model. A long-standing issue of nutrient trapping in the intermediate depth of the equatorial Pacific persists. Here, the simulated phosphate concentration is still higher than observed, but the bias is less severe than that of NorESM1. Consistently, dissolved inorganic carbon is still anomalously high and oxygen too low in the same region. The simulated Southern Ocean still has a too strong ventilation, leading to biases in the newly formed bottom watermass. Other physical biases such as the Antarctic Bottom Water penetrating far north also contributes to the simulated model-data differences in the interior North Atlantic.

Currently, evaluations of ocean biogeochemical components in ESMs have been largely focused on assessing the model ability in simulating the mean climatological state. However, further options exist (Eyring et al., 2016b; Heinze et al., 2019). The ocean biogeochemical observing community has put a lot of effort in sustaining key monitoring networks, such as the Surface CO_2 Atlas (SOCAT; Bakker et al., 2014) and the Global Ocean Data Analysis Project (GLODAP; Olsen et al., 2016). This critical observational network has provided additional valuable constraints for ESMs, such as by confronting the model ability to simulate seasonality of surface ocean pCO_2 as well as long-term trends in surface ocean pCO_2 (Tjiputra et al., 2014), ocean acidification (Lauvset et al., 2016), and deoxygenation (Tjiputra et al., 2018). As ESMs simulate emerging climate change signals in the coming decades (Henson et al., 2017), sustaining these observations into the future is becoming more important than ever.

In order to tackle the challenges associated with climate change, ocean modules in Earth system models could be further upgraded to include interactive methane (CH_4), nitrous oxide (N_2O), and biogenic volatile organic compounds (BVOCs) cycles for enabling model projections in respective emission driven frameworks. Moreover, NorESM2 still has a relatively simple marine biology that would benefit from more key functional groups as well as their sensitivity to climatic stressors. In preparation for the anticipated increasing spatial resolution in the physical components of the model, different data assimilation methods (combined with state-parameter estimation on the basis of observations) are currenty being explored to enable us to perform optimization of the current ecosystem parameterization more efficiently (Tjiputra et al., 2007; Gharamti et al., 2017).

Further NorESM-internal improvements may consider online estimated or progonostic organic carbon emissions from the ocean biogeochemistry to the atmosphere. Currently, we use fixed particulate organic carbon emissions from the ocean, linked to an upper-ocean chlorophyll-a climatology. The spatial distribution and temporal characteristics of DMS emissions may have an impact on the strength of the feedback involving DMS and aerosol-cloud interactions. Dust and iron or phosphate contained therein as well as nitrogen deposition will be computed in the future version of the atmospheric NorESM module and may provide more realistic nutrient input and may thus lead to feedbacks in a coupled ESM. The biogeochemical exchange processes are also dependent on sea ice cover and require better knowledge of air-sea-interaction processes in polar and subpolar regions. Mineralization processes in land regions may change under climate change conditions, leading to important changes in nutrient fluxes into the ocean biogeochemical systems. Biogenic Volatile Organic Compounds (BVOC) and halocarbons emitted from

the ocean have been suspected to influence atmospheric chemistry, e.g., in the stratosphere. It will certainly be the ambition of further developments to investigate the sensitivity of these processes to climate change to increase complexity where needed.

Beyond their current applications, future ESMs should be developed further to provide societal relevant information that is directly relevant for policy decisions on climate mitigation and adaptation measures. This includes potential climate hazards to societies (such as marine heatwaves, sudden pH drops, and spreading low oxygen zones in the oceans) as well as the risks emerging from the combination of hazards, vulnerabilities, and exposures (Oppenheimer et al., 2014). Future inclusion of socio-economic dynamics in ESMs and their feedback to climate through societal transformative action remains a big challenge (Giupponi et al., 2013) while a new ocean related socio-economic scenario framework (OSPs) has been developed mirroring the established Socioeconomic Pathways or SSPs (Maury et al., 2017). On the other hand, refining process complexity and increasing resolution may not be the only alternative for further model development, as the results of more complex model simulations become more difficult to interpret (Bony et al., 2011). Therefore, simplified models and ESMs of intermediate complexity including the respective simplified ocean biogeochemistry modules, will need to be developed and used in parallel (for instance Steinacher et al., 2013).

Data availability. All observational data used in this paper are publicly available: World Ocean Atlas (https://www.nodc.noaa.gov/OC5/woa13/), Global Ocean Data Analysis Project version 2 (https://www.glodap.info/), surface mixed layer depth (http://www.ifremer.fr/cerweb/deboyer/mld/home.php), surface pCO_2 and air-sea CO_2 fluxes (https://www.nodc.noaa.gov/ocads/oceans/SPCO2_1982_2011_ETH_SOM_FFN.html), ocean primary production (https://www.science.oregonstate.edu/ocean.productivity/), Dimethyl Sulphide (https://www.bodc.ac.uk/solas_integration/implementation_products/group1/dms/), $\Delta^{14}C$ and CFC-11 (https://www.nodc.noaa.gov/ocads/oceans/glodap/), and $\delta^{13}C$ (https://www.bcdc.no/data-products.html).

Code and data availability. The codes of Bergen Layered Ocean Model and isopycnic-based Hamburg Oceanic Carbon Cycle (BLOM-iHAMOCC) can be downloaded from https//github.com/NorESMhub/BLOM. The NorESM CMIP5 and CMIP6 model outputs can be accessed through the Earth System Grid Federation (ESGF) decentralized database (https://esgf-node.llnl.gov).

Table 1. Parameter values of the ecosystem parameterizations that have been changed between NorESM1, NorESM-OC1.2, and NorESM2. NorESM-OC1.2 was an intermediate model version (Schwinger et al., 2016) and is included here for completeness and traceability. Naming of parameters follows Ilyina et al. (2013).

Parameter	Symbol	NorESM1	NorESM-OC1.2	NorESM2	Unit
Half-saturation constant PO_4 uptake	K_{PO_4}	2×10^{-7}	4×10^{-8}	4×10^{-8}	$kmol\,P\,m^{-3}$
Half-saturation constant grazing	K_{zoo}	4×10^{-8}	4×10^{-8}	8×10^{-8}	$kmol\,P\,m^{-3}$
Half-saturation constant silicate uptake	K_{Si}	1.5×10^{-6}	1×10^{-6}	5×10^{-6}	$kmol\,Si\,m^{-3}$
Phytoplankton mortality rate	λ_{phy}	0.008	0.008	0.004	d^{-1}
Zooplankton mortality rate	λ_{zoo}	5×10^{-6}	3×10^{-6}	3×10^{-6}	$(kmol\,P\,m^{-3}\,d)^{-1}$
Phytoplankton exudation rate	β_{phy}	0.03	0.03	0.04	d^{-1}
Zooplankton excretion rate	β_{zoo}	0.03	0.06	0.06	d^{-1}
Maximum grazing rate	μ_{zoo}	1	1	1.2	–
Zooplankton assimilation efficiency	ω_{zoo}	0.5	0.6	0.7	–
Silicate to phosphorus uptake ratio	$R_{Si:P}$	25	30	33	$mol\,Si\,mol\,P^{-1}$
$CaCO_3$ to phosphorus uptake ratio	$R_{CaCO_3:P}$	35	40	45	$mol\,CaCO_3\,mol\,P^{-1}$
Fraction of grazing ingested	ε_{zoo}	0.8	0.8	0.85	–
Detritus remineralization rate	λ_{det}	0.03	0.025	0.025	d^{-1}
DOC remineralization rate	λ_{DOC}	0.025	0.025	0.004	d^{-1}

Table 2. List of the simulated variables and the respective historical simulation periods over which their climatological values have been averaged. The last column indicates the observational reference used to validate the model output.

Model variables	Periods	Observations and references
Temperature	1971–2000	World Ocean Atlas 2013 (Locarnini et al., 2013)
Salinity	1971–2000	World Ocean Atlas 2013 (Zweng et al., 2013)
Mixed layer depth	1971–2000	de Boyer Montégut et al. (2004)
Oxygen	1971–2000	World Ocean Atlas 2013 (Garcia et al., 2013a)
Phosphate	1971–2000	World Ocean Atlas 2013 (Garcia et al., 2013b)
Nitrate	1971–2000	World Ocean Atlas 2013 (Garcia et al., 2013b)
Silicate	1971–2000	World Ocean Atlas 2013 (Garcia et al., 2013b)
Dissolved inorganic carbon	1997–2007	Global Ocean Data Analysis Project (GLODAPv2; Lauvset et al., 2016)
Alkalinity	1997–2007	Global Ocean Data Analysis Project (GLODAPv2; Lauvset et al., 2016)
Surface pCO_2	1982–2011	Landschützer et al. (2015)
Sea-air CO_2 fluxes	1982–2011	Landschützer et al. (2015)
Net primary production	2003–2012	Averaged of the three remote sensing products (VGPM, Eppley-VGPM, and CbPM) from Moderate Resolution Imaging Spectroradiometer (Behrenfeld and Falkowski, 1997; Westberry et al., 2008)
Dimethyl sulfate	1971–2000	Lana et al. (2011)
CFC-11	2000	Key et al. (2004)
$\delta^{13}C$	Last 10 yrs of piControl	Eide et al. (2017)
$\Delta^{14}C$	Last 10 yrs of piControl	Key et al. (2004)

Table 3. Annual mean biology-related metrics simulated by NorESM1-ME, NorESM2-LM, and NorESM2-MM.

	NorESM1-ME	NorESM2-LM	NorESM2-MM	Units
Primary production	39.86	33.27	35.29	Pg C yr^{-1}
POC export	7.90	4.94	5.39	Pg C yr^{-1}
$CaCO_3$ export	0.49	0.66	0.74	Pg C yr^{-1}
Opal export	105.93	76.89	81.38	Tmol Si yr^{-1}
f-ratio	0.20	0.15	0.15	-
$CaCO_3$ to POC ratio	0.06	0.13	0.14	-
$T_{eff-1km}$	0.06	0.24	0.24	-

Table 4. Annual and cumulated ocean carbon uptakes simulated by NorESM1, NorESM2, and from observation-based estimates.

	NorESM1-ME	NorESM2-LM	NorESM2-MM	Observations
Annual uptake 1980s [Pg C yr^{-1}]	2.03	1.80	1.85	1.8±0.8 (Denman et al., 2007)
Annual uptake 1990s [Pg C yr^{-1}]	2.24	2.04	2.05	2.2±0.4 (Denman et al., 2007)
Cumulated uptake (1850-1994) [Pg C]	127.91	111.02	107.82	111±21* (Gruber et al., 2019)
Cumulated uptake (1994-2007) [Pg C]	33.68	30.57	31.04	29±5 (Gruber et al., 2019)

*1800-1994
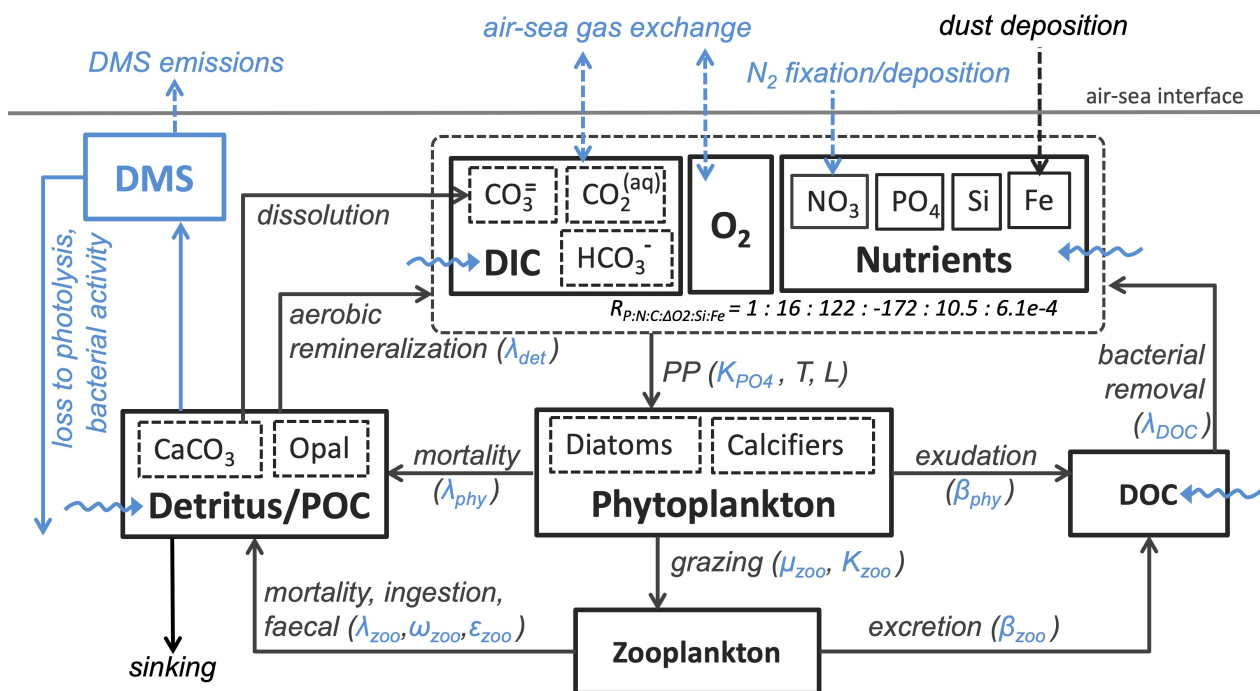
Figure 1. Schematic diagram of the ecosystem module in the ocean biogeochemical component of the NorESM2 model. The diagram is an updated version of a similar diagram in Six and Maier-Reimer (2006). Blue depicts components, processes, and parameters that have been modified in NorESM2 relative to the previous model version NorESM1-ME. Dashed-arrows indicate air-sea interactions, while wavy arrows depict riverine inputs.
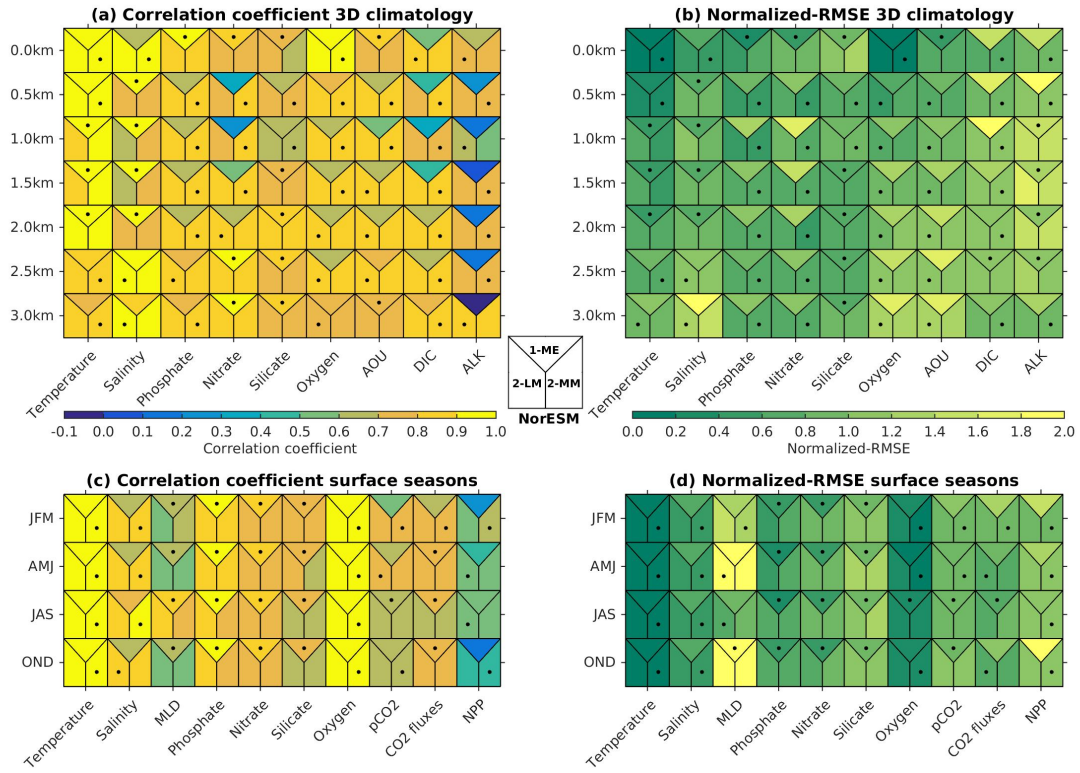
Figure 2. Summary of (a,c) spatial correlation coefficients and (b,d) normalized-RMSE between the observations and models (NorESM1-ME, NorESM2-LM and NorESM2-MM). In all (a,b) 3D fields, the metric values are computed over a 2D horizontal global domain ranging from the surface to 3km depth for 3D fields, while for (c,d) seasonal metrics, only surface values are evaluated. Each square contains three metric scores, i.e., for NorESM1-ME (top), NorESM2-LM (bottom-left), and NorESM2-MM (bottom-right). Black dots indicate which model performes the best.
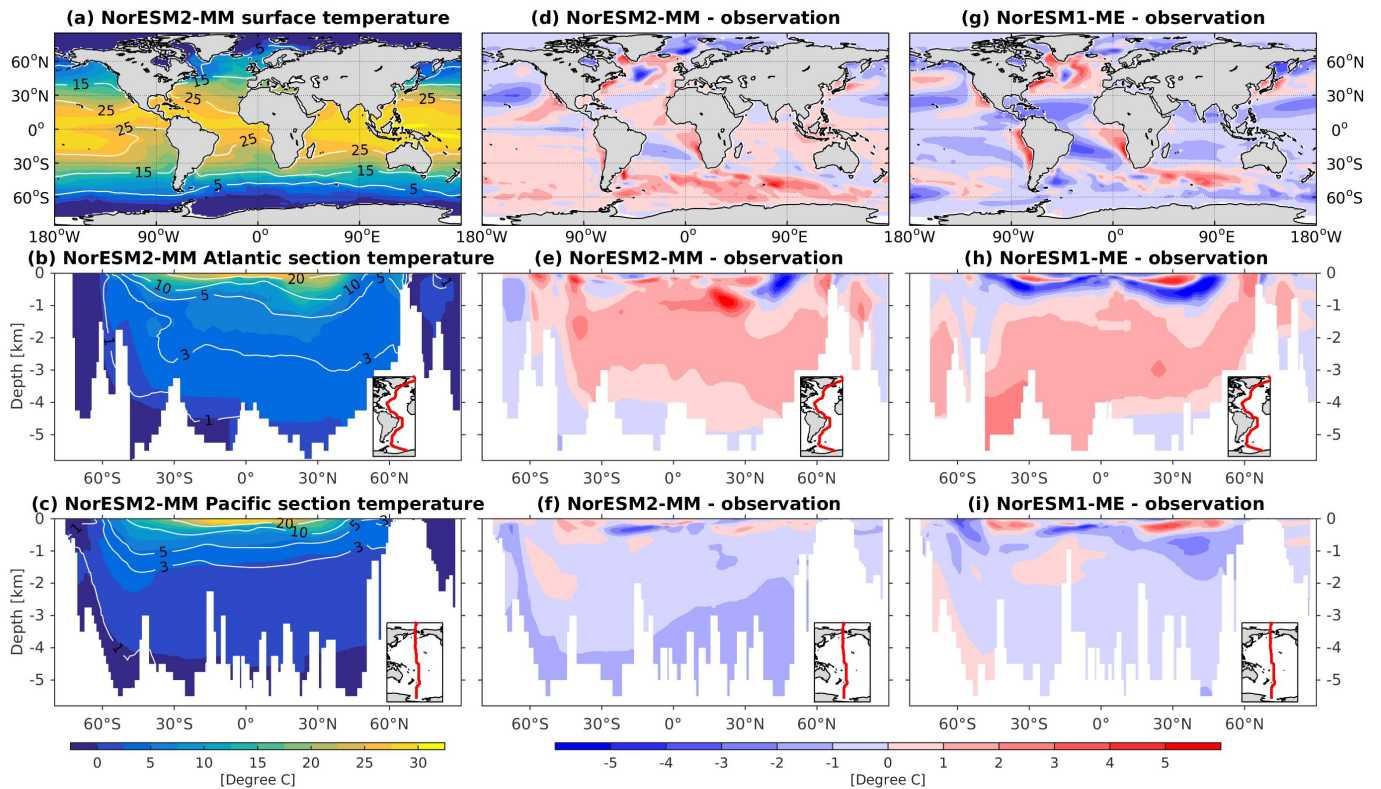
Figure 3. Climatological temperature values at the (a) surface and across the vertical sections of (b) Atlantic and (c) Pacific in NorESM2-MM (color-shadings) and from observations (contour lines). Differences between NorESM2-MM (or NorESM1-ME) and observations are shown in panels (d)-(i).
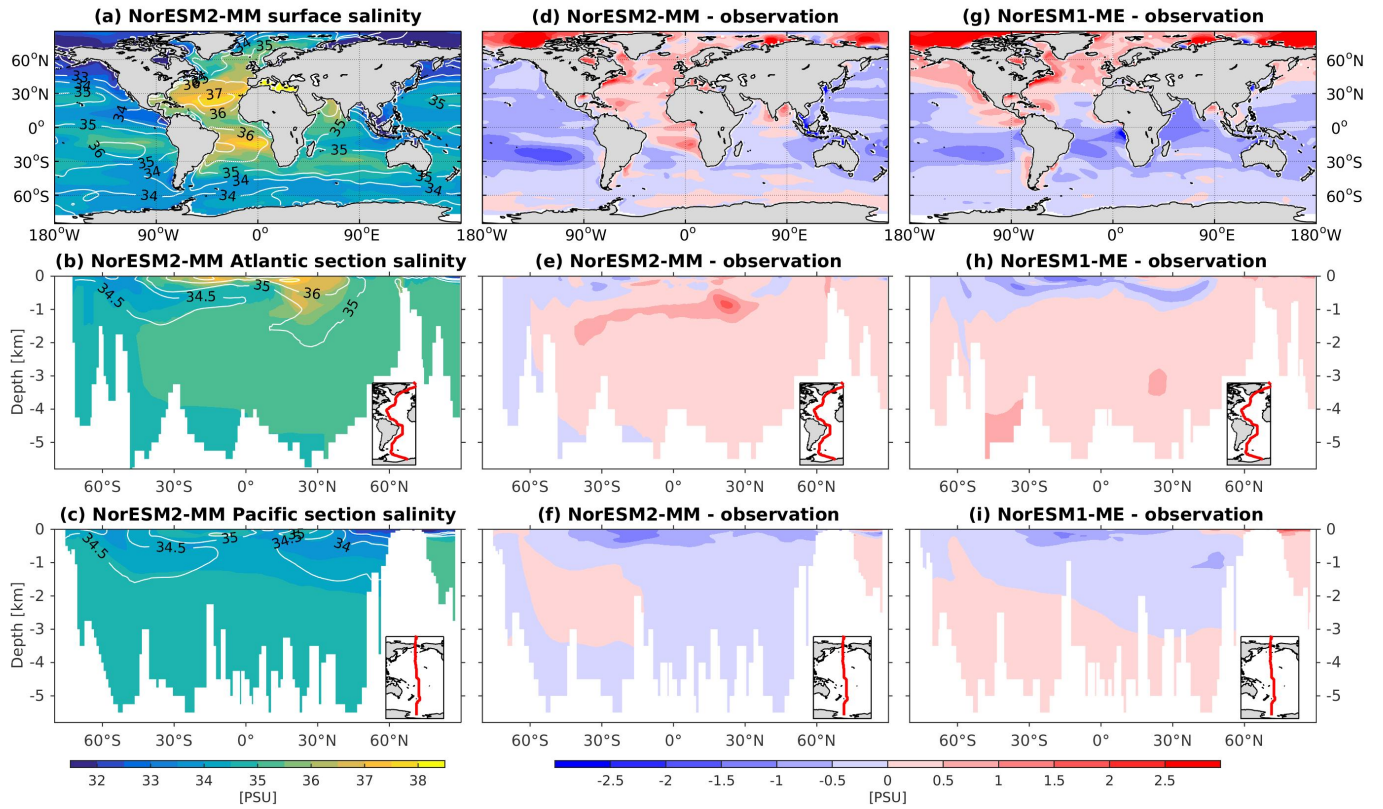
Figure 4. Climatological salinity values at the (a) surface and across the vertical sections of (b) Atlantic and (c) Pacific in NorESM2-MM (color-shadings) and from observations (contour lines). Differences between NorESM2-MM (or NorESM1-ME) and observations are shown in panels (d)-(i).
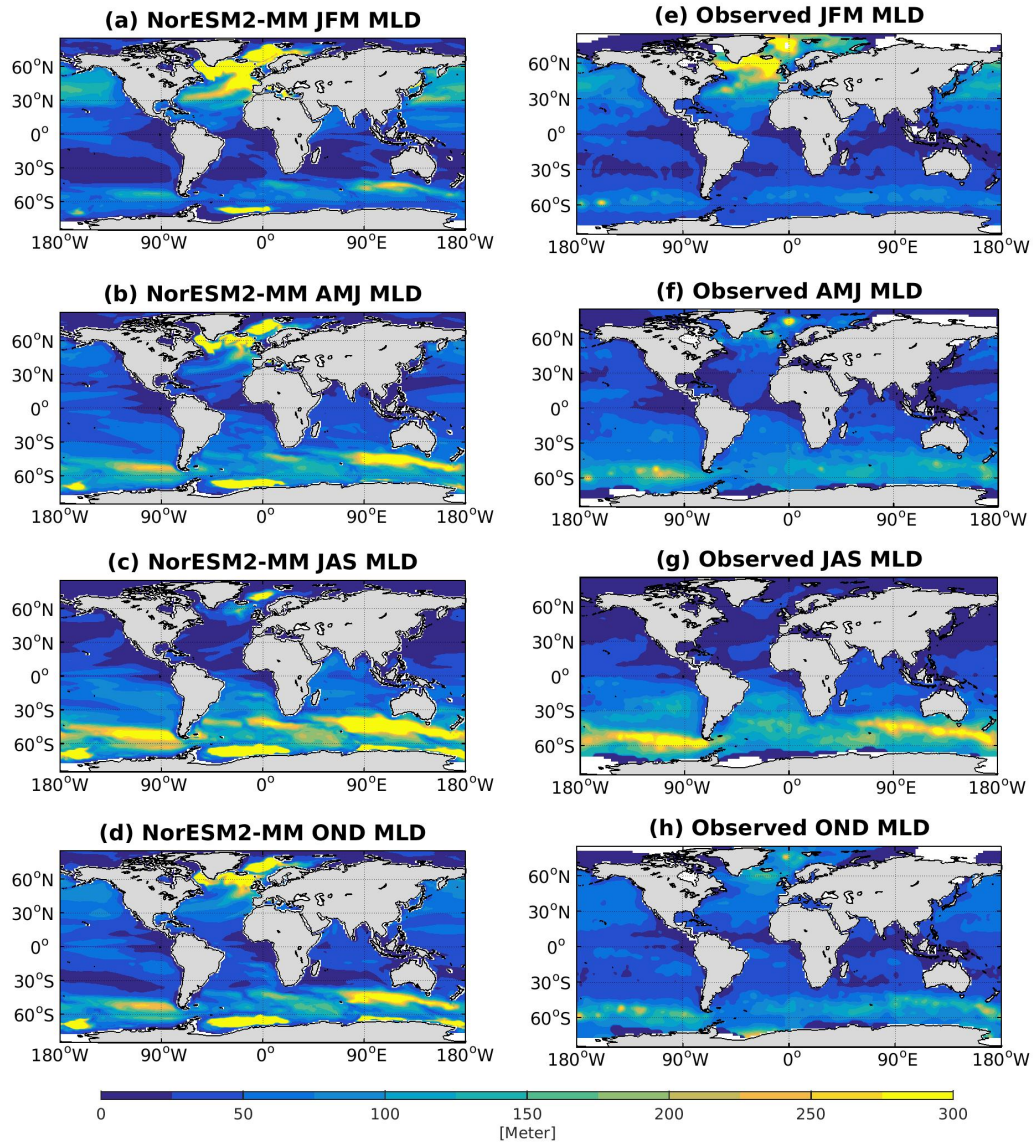
Figure 5. Climatological seasonal mixed layer depth as (left-column) simulated in NorESM2-MM and (right-column) estimated from observations.
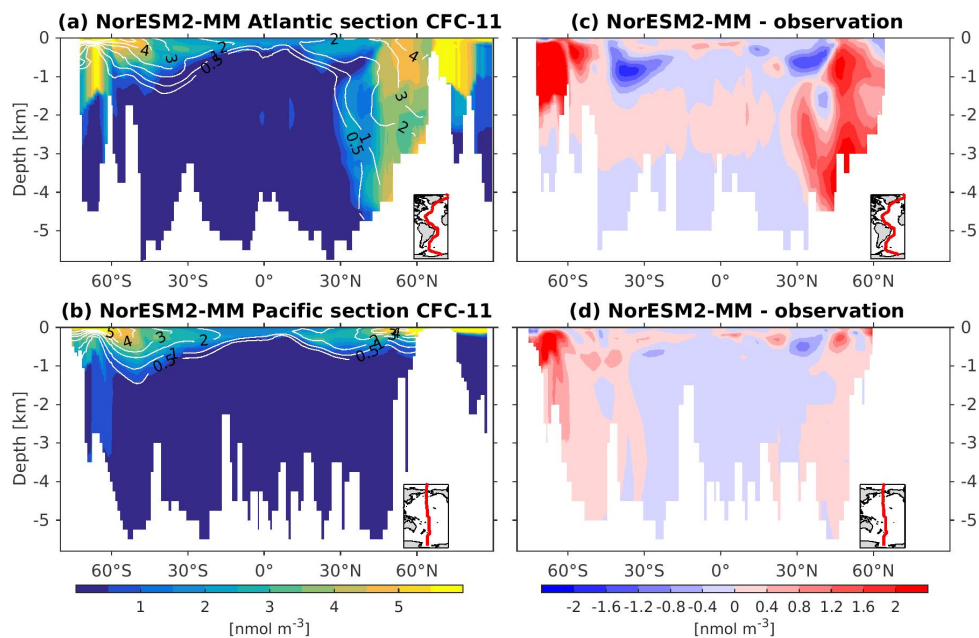
Figure 6. Concentration of CFC-11 across the vertical sections of (a) Atlantic and (b) Pacific from NorESM2-MM (color-shadings) and observations (contour lines). Differences between NorESM2-MM and observations are shown in panels (c)-(d).
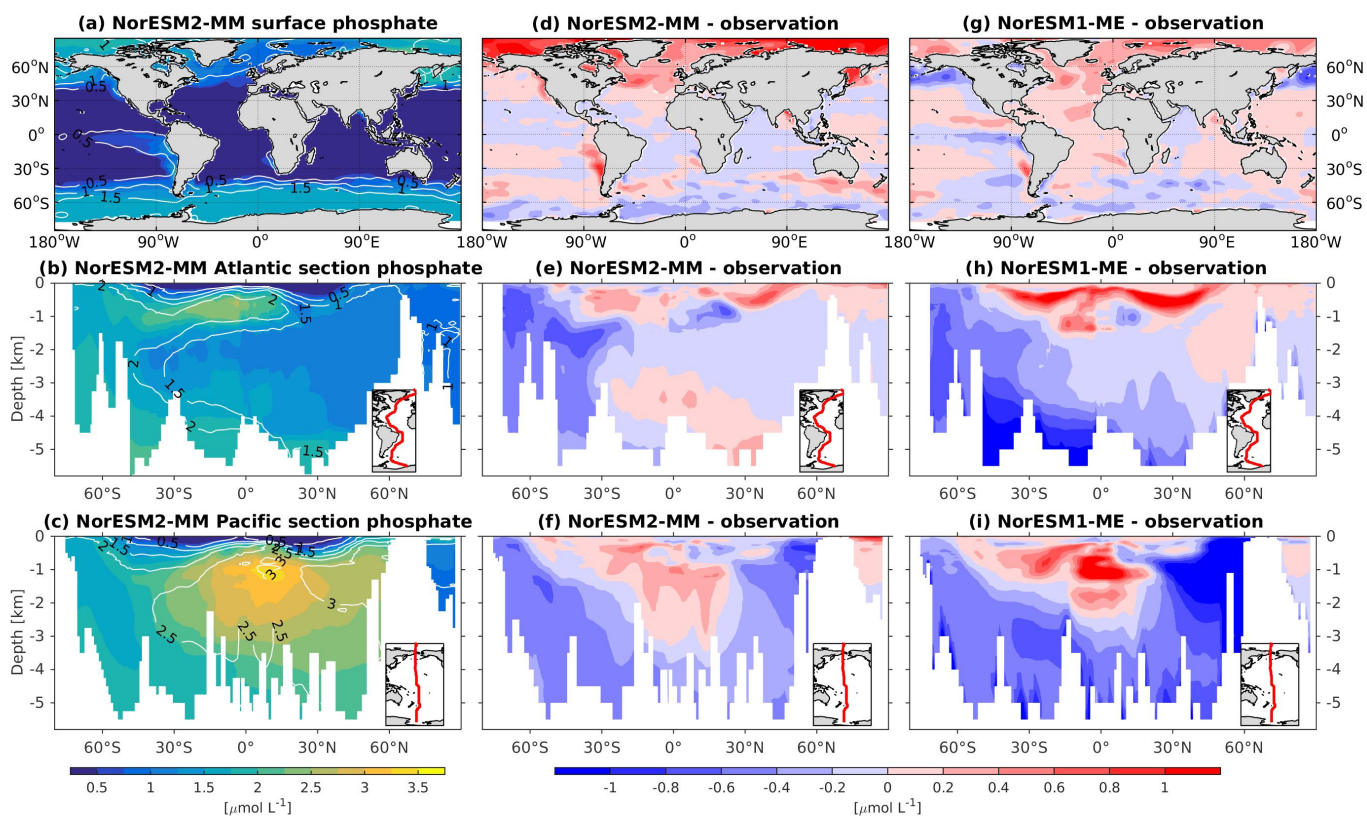
Figure 7. Climatological phosphate values at the (a) surface and across the vertical sections of (b) Atlantic and (c) Pacific in NorESM2-MM (color-shadings) and from observations (contour lines). Differences between NorESM2-MM (or NorESM1-ME) and observations are shown in panels (d)-(i).
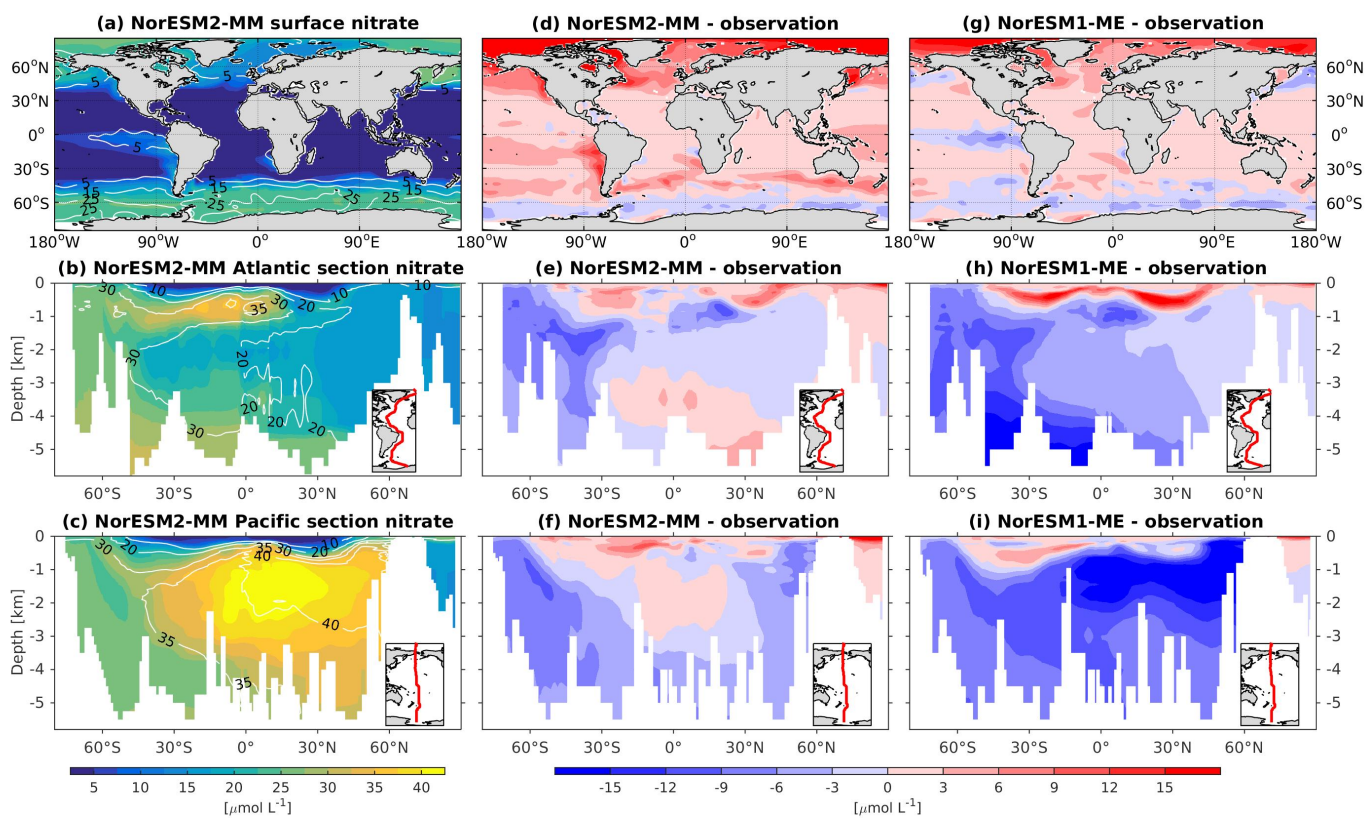
Figure 8. Climatological nitrate values at the (a) surface and across the vertical sections of (b) Atlantic and (c) Pacific in NorESM2-MM (color-shadings) and from observations (contour lines). Differences between NorESM2-MM (or NorESM1-ME) and observations are shown in panels (d)-(i).
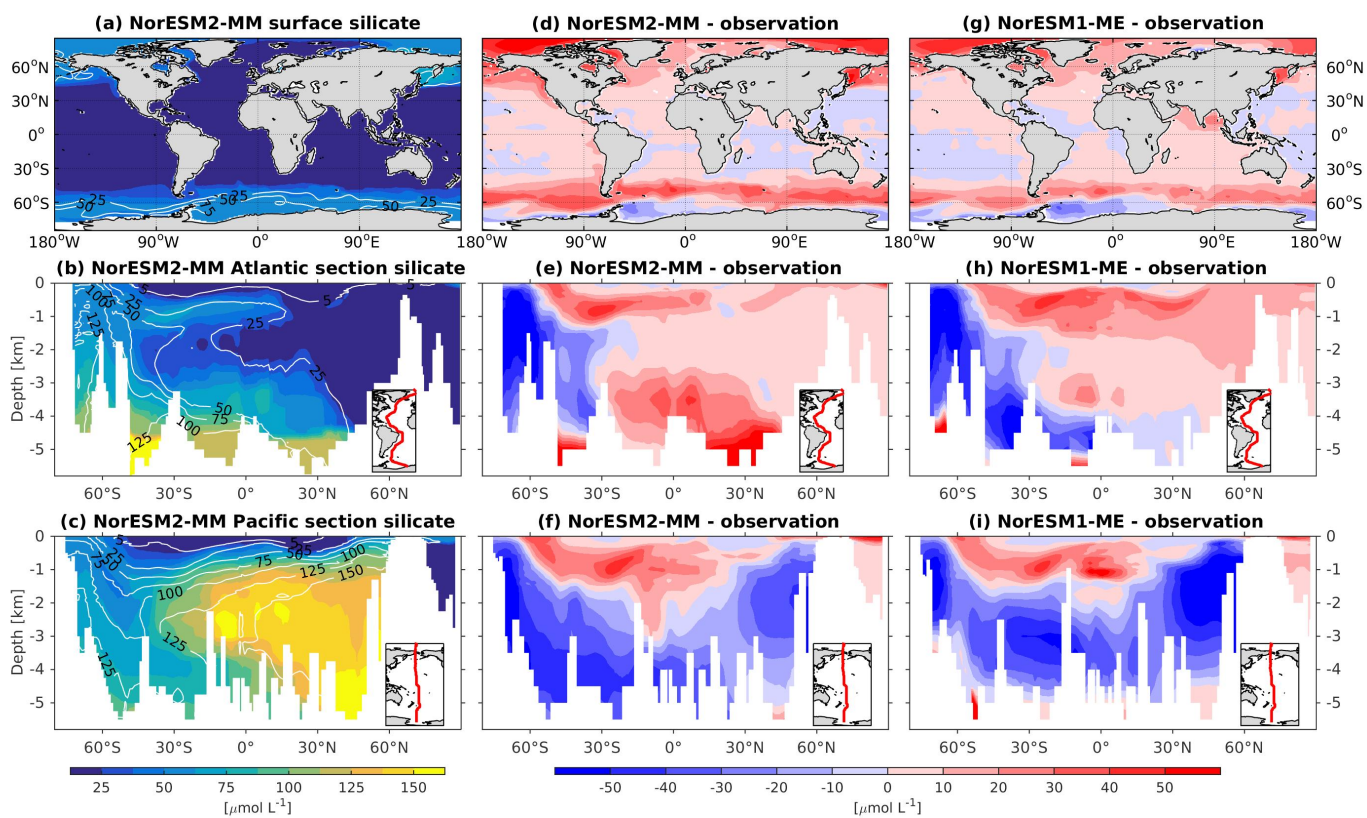
Figure 9. Climatological silicate values at the (a) surface and across the vertical sections of (b) Atlantic and (c) Pacific in NorESM2-MM (color-shadings) and from observations (contour lines). Differences between NorESM2-MM (or NorESM1-ME) and observations are shown in panels (d)-(i).
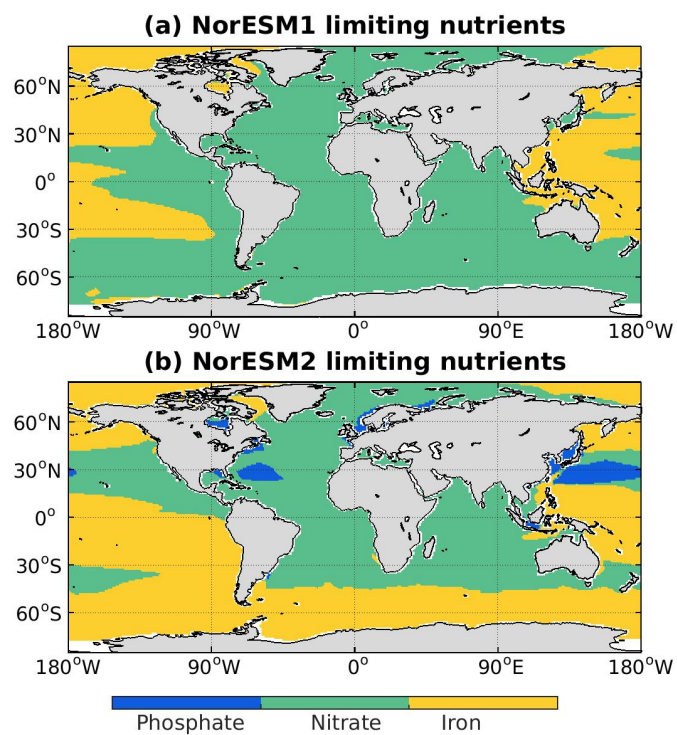
Figure 10. Maps of limiting nutrients for biological productivity as simulated in (a) NorESM1 and (b) NorESM2. The limiting nutrient is determined as the minimum between PO_4, $R_{P:N} \cdot NO_3$, and $R_{P:Fe} \cdot Fe$.
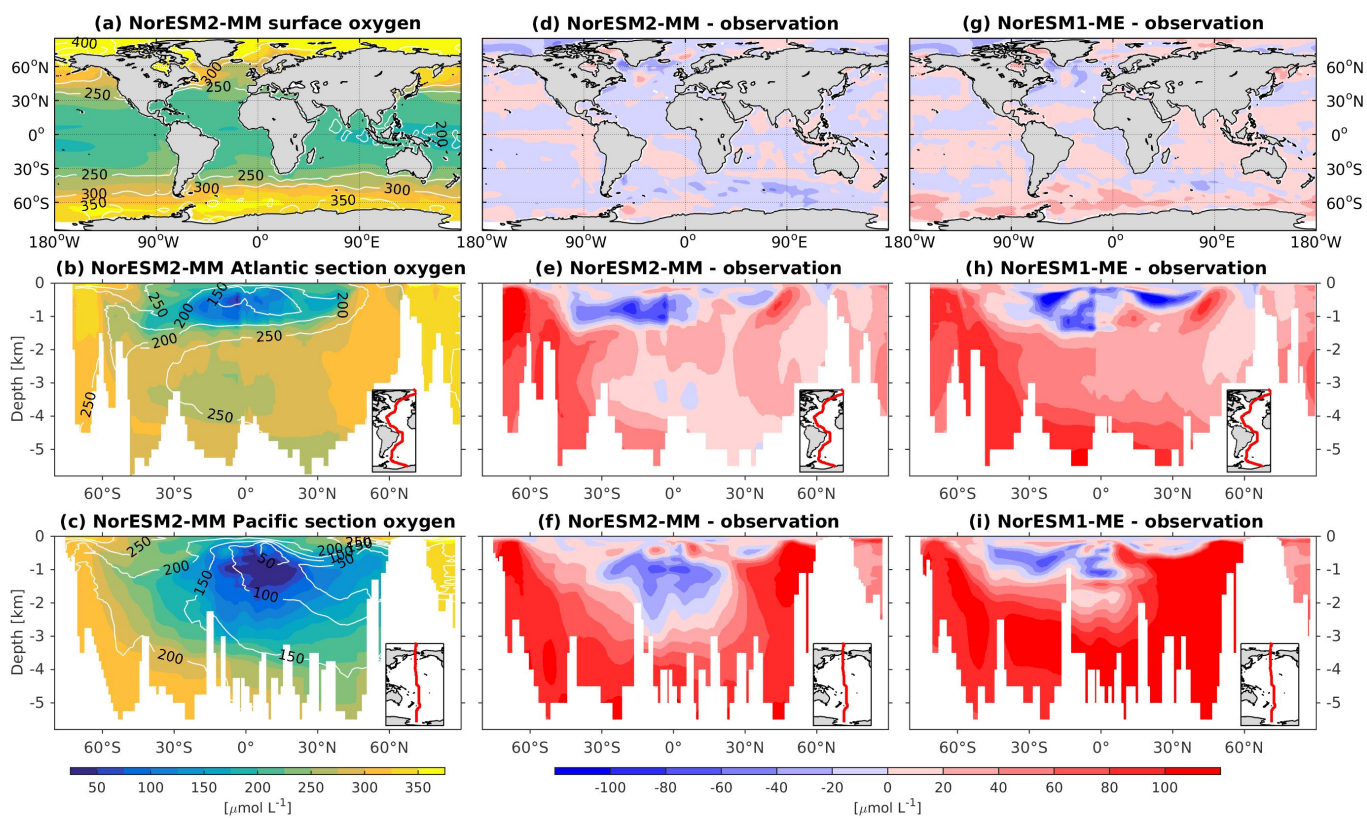
Figure 11. Climatological dissolved oxygen values at the (a) surface and across the vertical sections of (b) Atlantic and (c) Pacific in NorESM2-MM (color-shadings) and from observations (contour lines). Differences between NorESM2-MM (or NorESM1-ME) and observations are shown in panels (d)-(i).
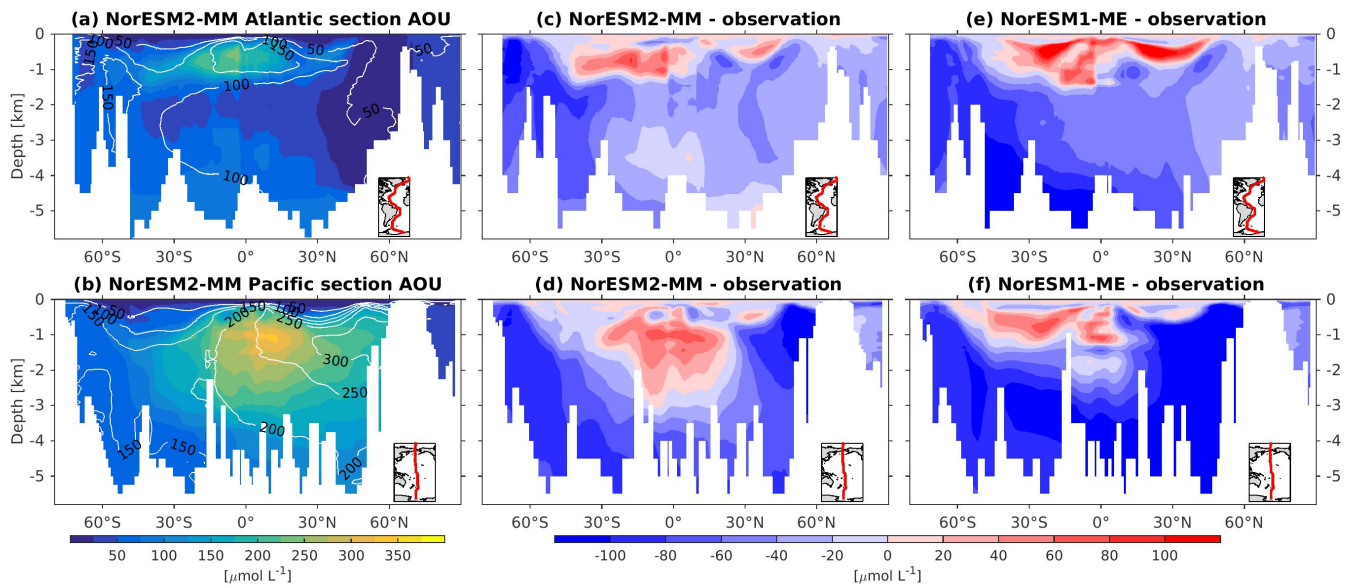
Figure 12. Climatology of apparent oxygen utilization (AOU) values across the vertical sections of (a) Atlantic and (b) Pacific in NorESM2 (color-shadings) and from observations (contour lines). Differences between NorESM2-MM (or NorESM1-ME) and observations are shown in panels (c)-(f).
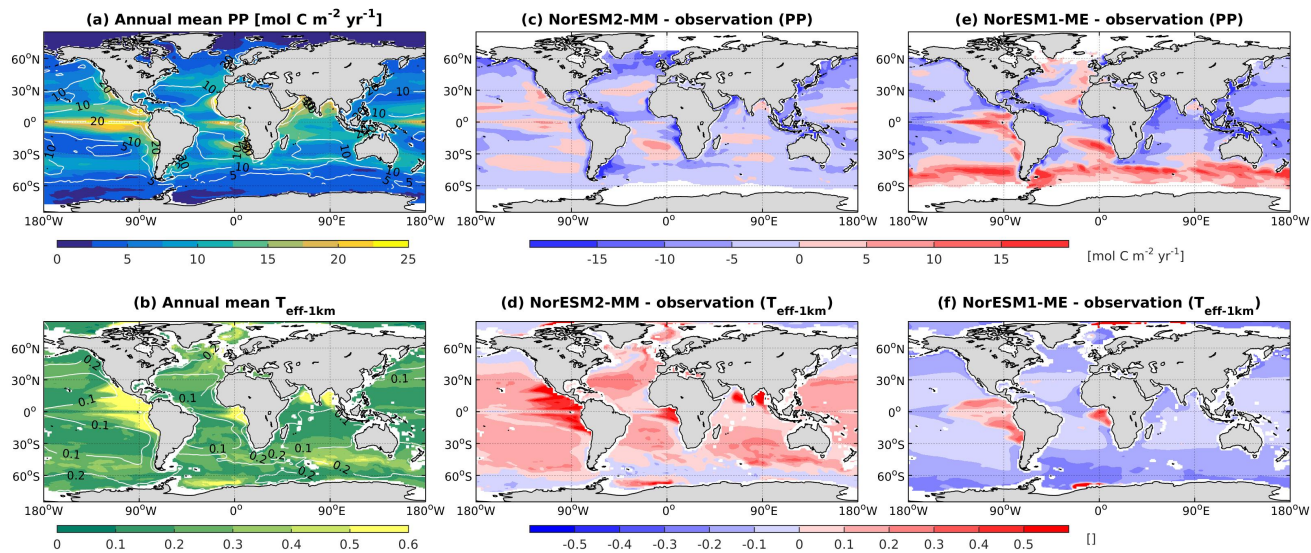
Figure 13. Annual mean (a) vertically-integrated contemporary primary production and (b) transfer efficiency ($T_{eff-1km}$) as simulated in NorESM2 (color-shadings) and from observations (contour-lines). Respective difference between NorESM2-MM (NorESM1-ME) and observations are shown in color-shadings (contour-lines) in panels (c)-(d).
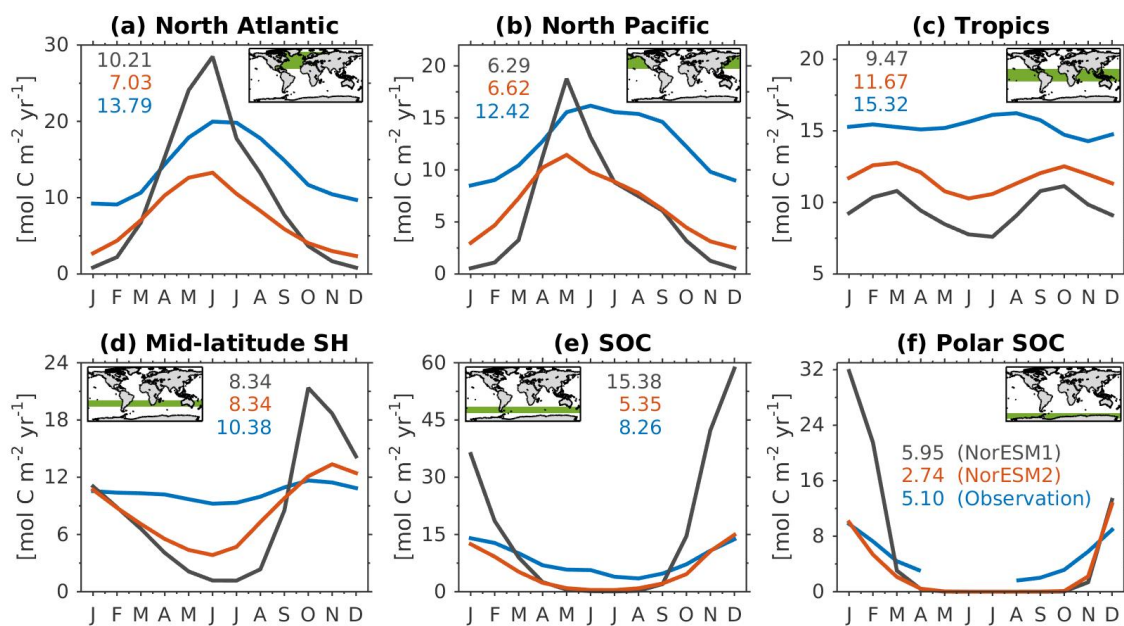
Figure 14. Mean seasonal cycle of vertically-integrated contemporary primary production in the (a) North Atlantic (north of 20°N), (b) North Pacific (north of 20°N), (c) tropics (20°S-20°N), (d) mid-latitude southern hemisphere (20°S-40°S), (e) Southern Ocean (40°S-60°S), and (f) polar Southern Ocean (south of 60°S). Shown are values from NorESM1-ME (black), NorESM2-MM (red) and observational estimates (blue). Numbers within each panel depict the regional mean values averaged over all months.
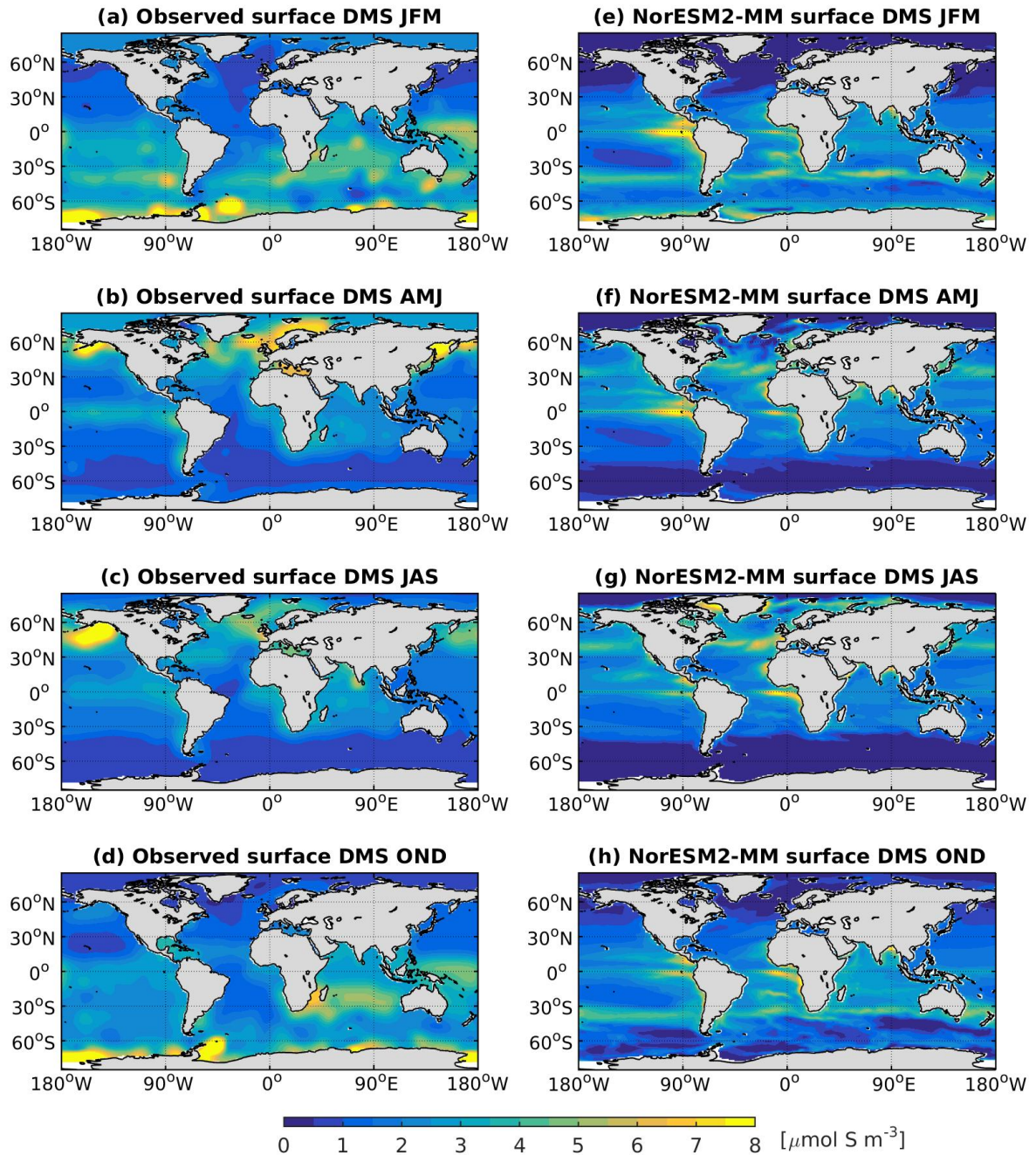
Figure 15. Seasonally-averaged surface concentration of DMS from observations (a-d) and as simulated in NorESM2-MM (e-h).
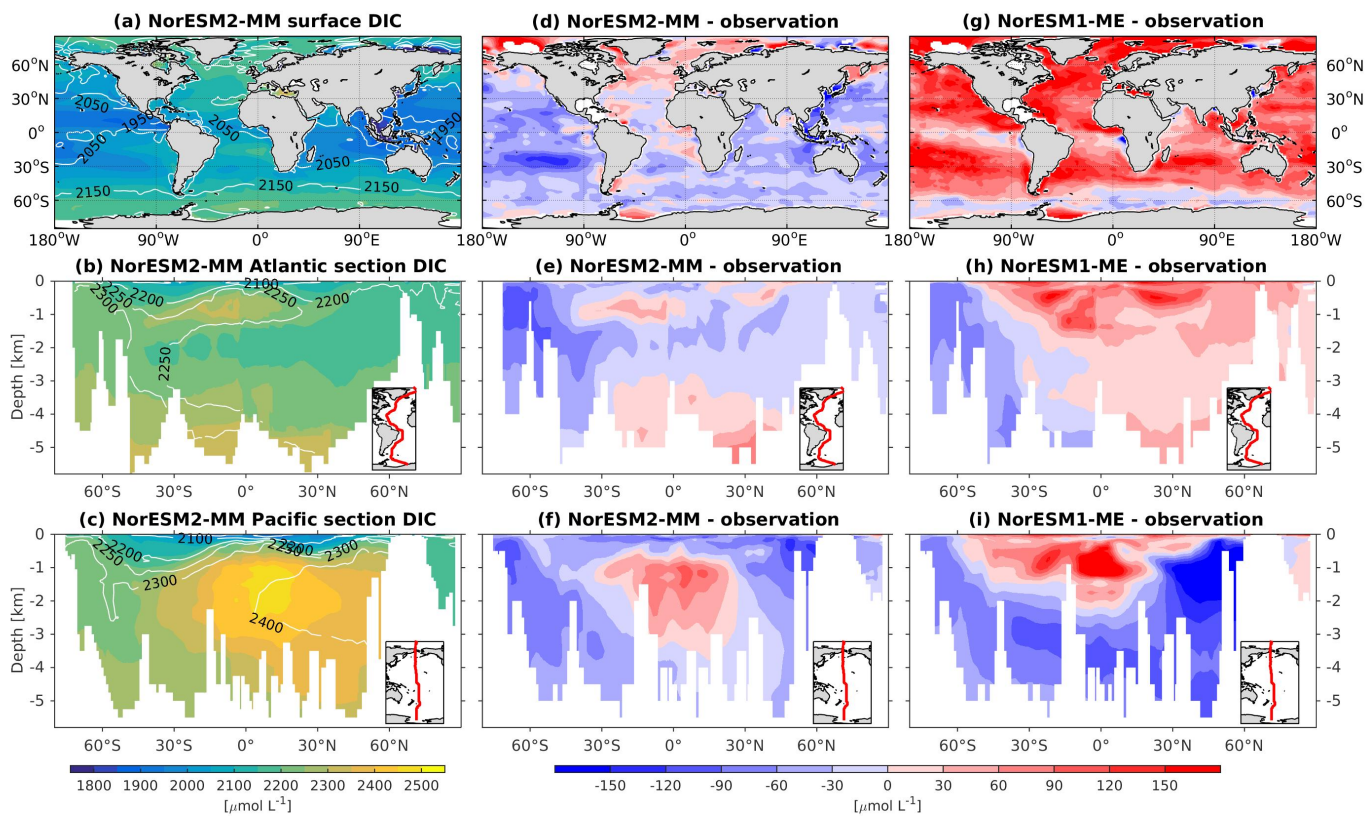
Figure 16. Climatological dissolved inorganic carbon (DIC) values at the (a) surface and across the vertical sections of (b) Atlantic and (c) Pacific in NorESM2-MM (color-shadings) and from observations (contour lines). Differences between NorESM2-MM (or NorESM1-ME) and observations are shown in panels (d)-(i).
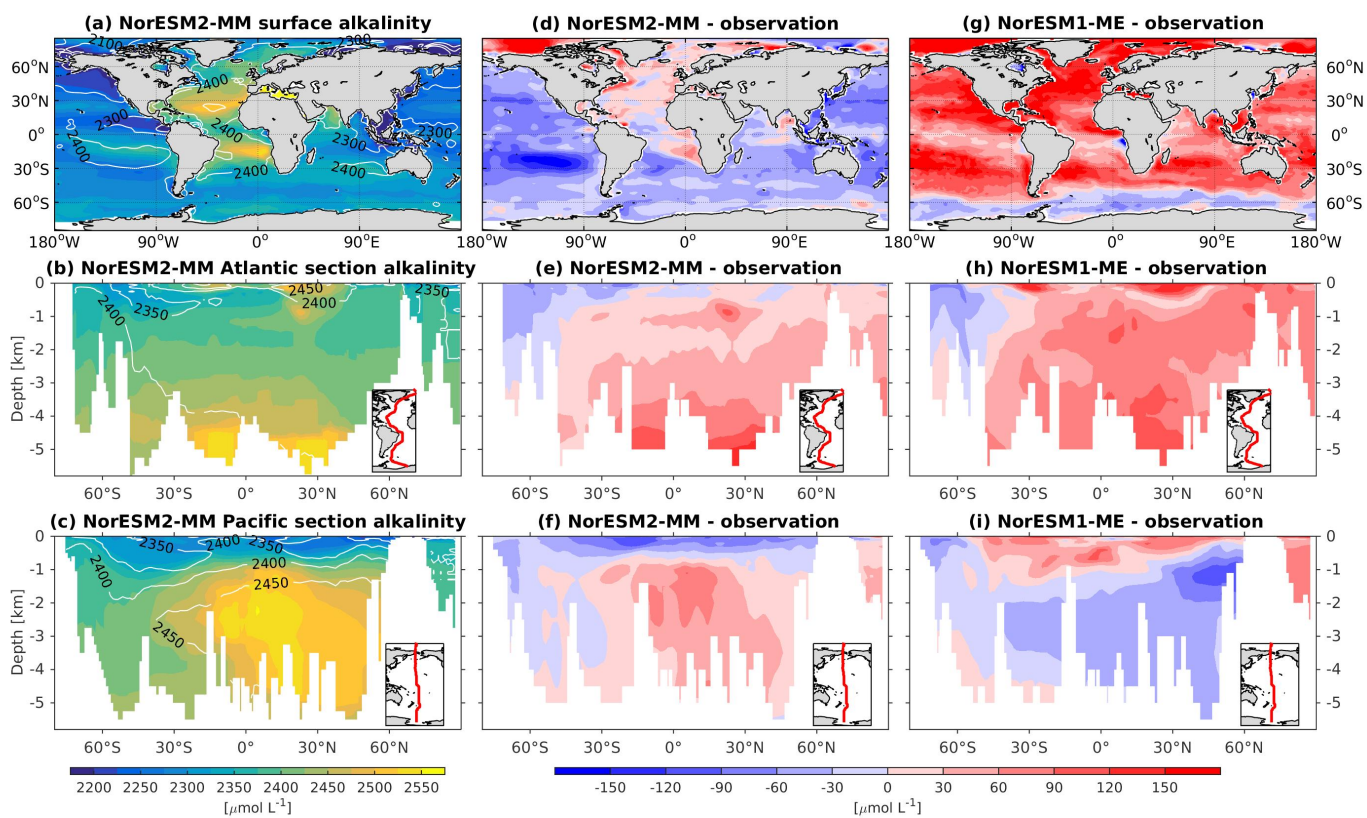
Figure 17. Climatological alkalinity values at the (a) surface and across the vertical sections of (b) Atlantic and (c) Pacific in NorESM2-MM (color-shadings) and from observations (contour lines). Differences between NorESM2-MM (or NorESM1-ME) and observations are shown in panels (d)-(i).
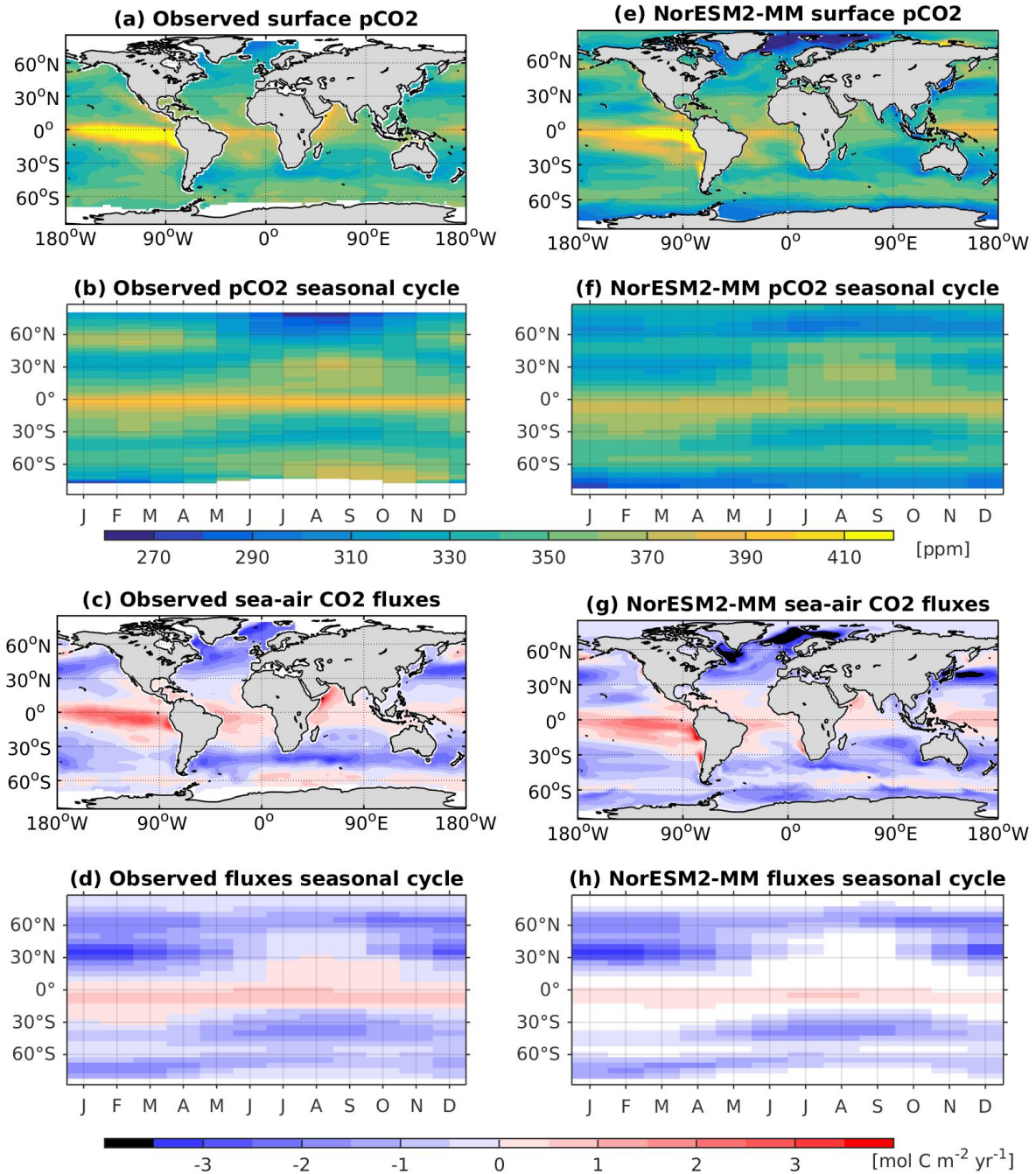
Figure 18. Observed surface climatology maps of (a) partial pressure of CO_2 and (c) sea-air CO_2 fluxes together with Hovmöller plots of zonally-averaged seasonal cycle of (b) surface pCO_2 and (d) sea-air CO_2. Corresponding values from NorESM2-MM simulation are shown in panels (e-g).
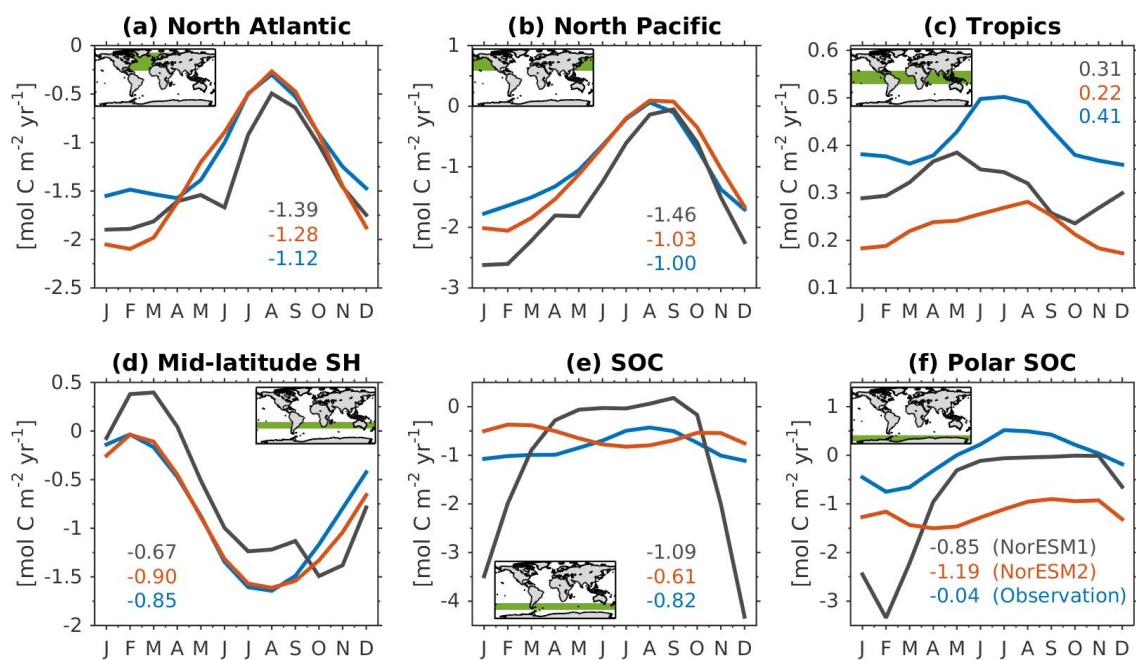
Figure 19. Mean seasonal cycle of vertically-integrated contemporary sea-to-air CO_2 fluxes in the (a) North Atlantic (north of 20°N), (b) North Pacific (north of 20°N), (c) tropics (20°S-20°N), (d) mid-latitude southern hemisphere (20°S-40°S), (e) Southern Ocean (40°S-60°S), and (f) polar Southern Ocean (south of 60°S). Shown are values from NorESM1-ME (black), NorESM2-MM (red) and observational estimates (blue). Numbers within each panel depict the regional mean values averaged over all months.
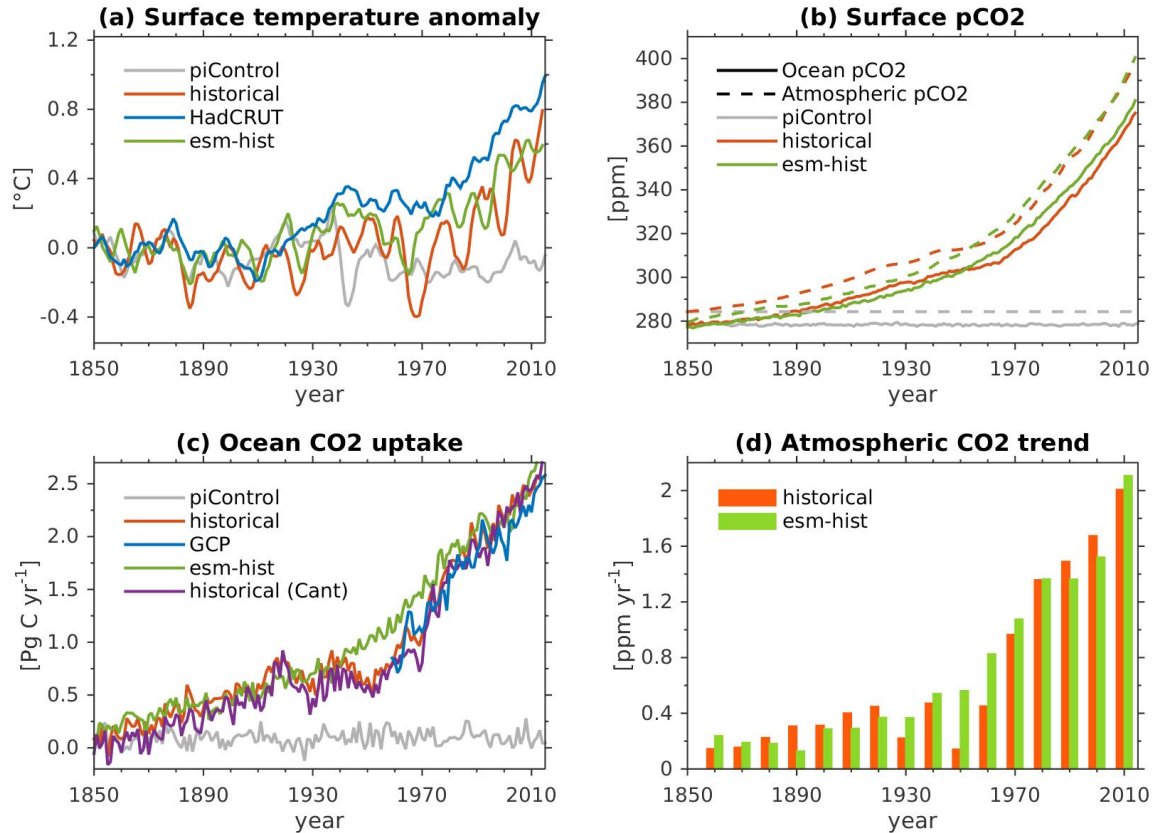
Figure 20. Time-series of global mean annual (a) surface air temperature anomalies relative to the 1850-1879 period, (b) surface ocean and atmospheric pCO$_2$, (c) ocean CO$_2$ uptake, and (d) atmospheric CO$_2$ concentration. Shown are values from NorESM2-MM (grey) preindustrial control and (orange) historical simulations. Green depicts results from the emissions prescribed historical simulation with NorESM2-LM. The purple line in panel (c) represents the anthropogenic carbon uptake estimated by substracting the natural carbon uptake from the total uptake (see also Section 3.2). Data for temperature and ocean carbon sinks are estimates from HadCRUT4 and the Global Carbon Project (Morice et al., 2012; Le Quéré et al., 2018), respectively, in blue colors.
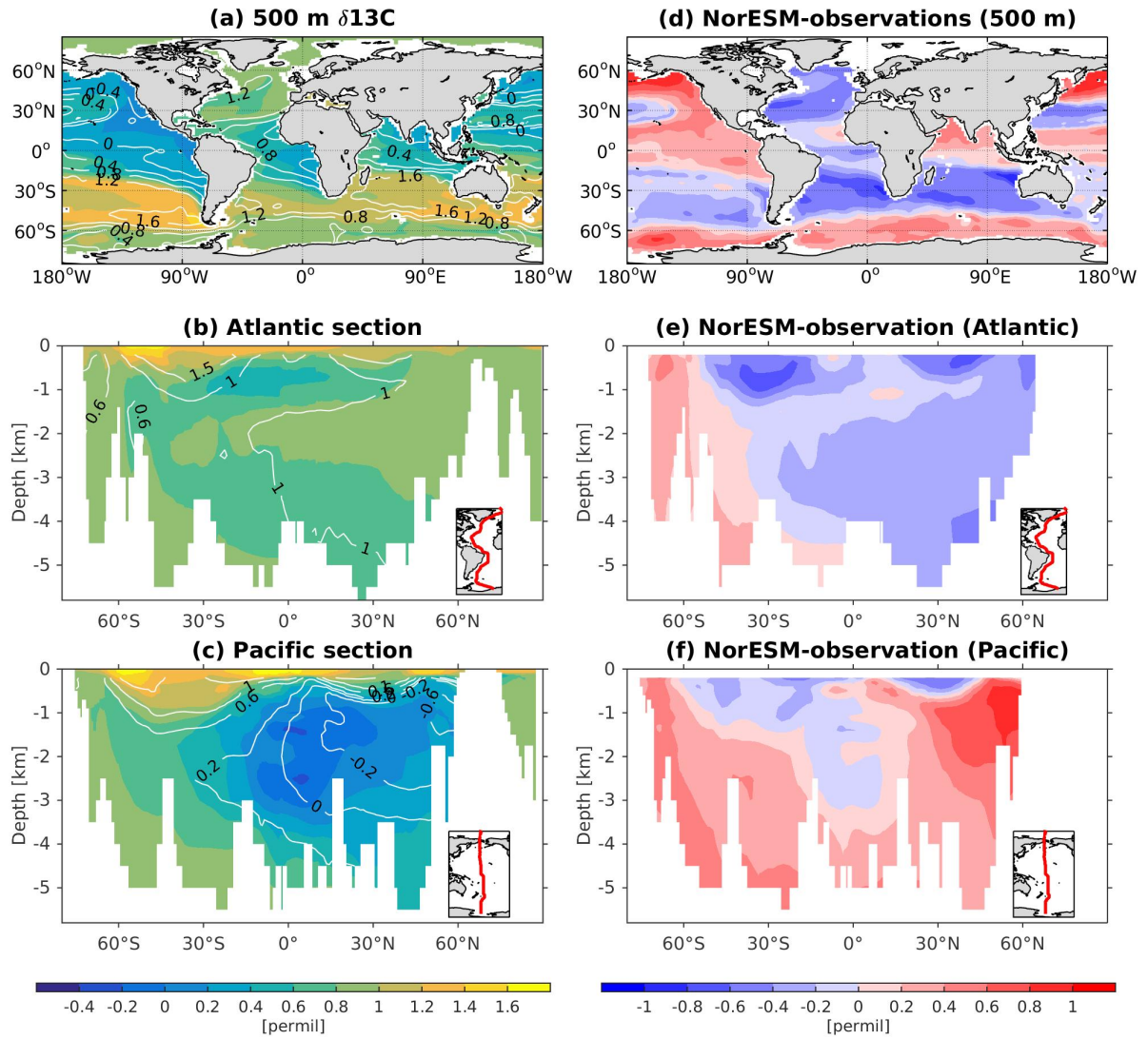
Figure 21. Climatological $\delta^{13}C$ values at (a) 500 m depth and across the vertical sections of (b) Atlantic and (c) Pacific from NorESM2-OC (color-shadings) and observations (contour lines). Differences between NorESM2-OC and observations are shown in color-shadings in panels (d)-(f).
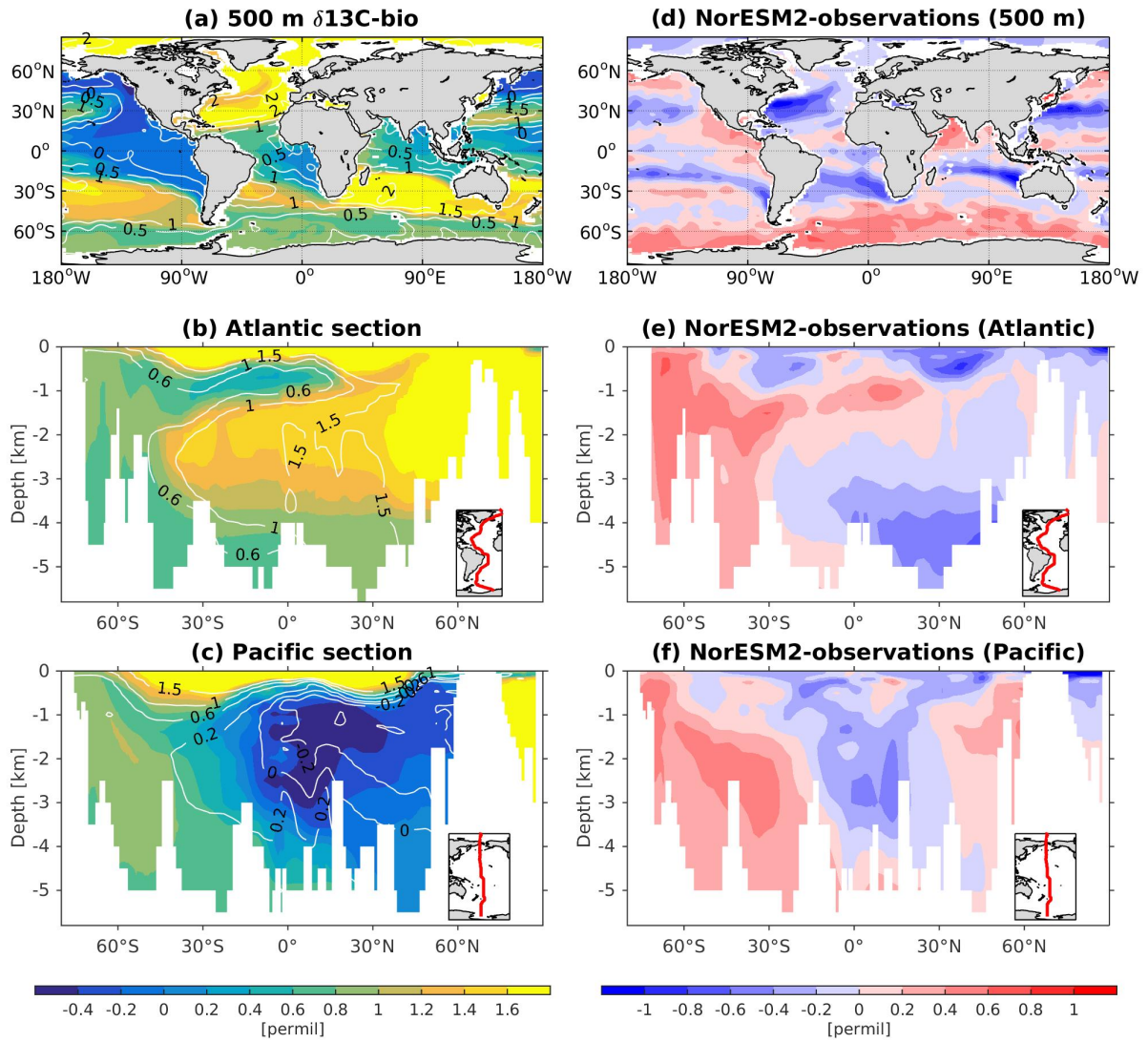
Figure 22. Climatological fields of the biological component of $\delta^{13}C$ (i.e., $\delta^{13}C_{BIO}$) at (a) 500 m depth and across the vertical sections of (b) Atlantic and (c) Pacific from NorESM2-OC (color-shadings) and observations (contour lines). Differences between NorESM2-OC and observations are shown in color-shadings in panels (d)-(f).
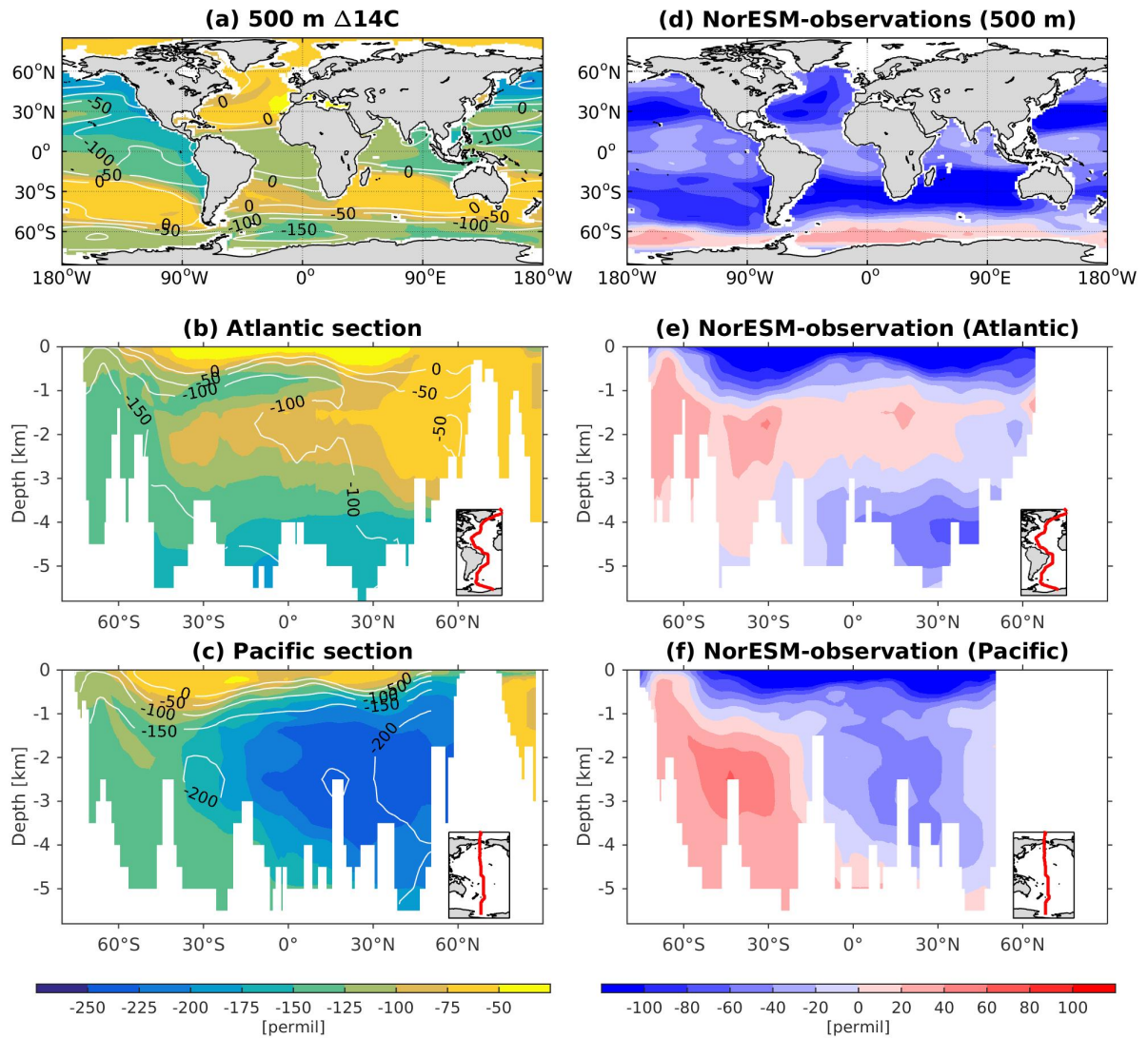
Figure 23. Climatology Δ^{14}C values at (a) 500 m depth and across the vertical sections of (b) Atlantic and (c) Pacific from NorESM2 (color-shadings) and observations (contour lines). Differences between NorESM2 and observations are shown in color-shadings in panels (d)-(f).

Appendix A

A1

Author contributions. JT, JS, AM, MB, CH, IB, and SG contributed to developing and implementing the iHAMOCC model code changes. JT, JS, MB, AM, AG, DO, and ØS designed, tested, and performed the experiments described in the manuscript. JT, JS, AM, and YH analyzed the model simulations. All authors contributed to the writing of the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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