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Final report on WP5.4: Seasonal predictability of ocean biogeochemistry and potential benefits of ESA CCI data assimilation

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Purpose and scope of this report

This document is the final report on WP5.4 ("Seasonal predictability of ocean biogeochemistry and potential benefits of ESA CCI data assimilation") of the CCI+ CMUG project.

WP5.4 aims to explore the potential benefits to our capacity to predict key ocean biogeochemical variables at seasonal time scales when ESA CCI products for physical fields (sea surface temperature, sea surface salinity, sea level, sea ice) and biogeochemical fields (ocean colour) are assimilated into state-of-the-art modelling systems. Two partners (Met Office and Barcelona Supercomputing Center) separately performed sets of experiments assimilating different combinations of ESA CCI products into the ocean physical-biogeochemical reanalysis configurations of their respective global seasonal forecasting systems. The results of these experiments have been inter-compared and conclusions drawn as to the optimal assimilation strategy for initialising seasonal forecasts of ocean biogeochemical variables, and the relative importance of satellite observations of physical and biogeochemical fields. Recommendations have been made, and the follow-on OWP5.4 will build on this work and run seasonal reforecasting experiments with the Met Office system.

This report is in the form of a draft journal paper, planned to be submitted for publication shortly.

Assimilation choices for global ocean physics-biogeochemistry reanalysis in the context of seasonal forecasting

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Abstract

Two global ocean physical-biogeochemical reanalysis systems were used to assess the impact of different assimilation configurations and satellite observation products on properties relevant to seasonal forecasting of global ocean biogeochemistry. Both physics and biogeochemistry satellite products showed potential to improve reanalyses and therefore seasonal forecasts of biogeochemistry, but only if used in ways that enabled multivariate and subsurface updates. Doing so helped maximise impact, but at times degraded model skill, demonstrating the need for careful design of such assimilation schemes.

1. Introduction

There is a growing need for seasonal predictions of variables which impact the marine ecosystem, such as primary production, pH, dissolved oxygen, and marine heatwaves. These can inform fisheries management decisions, and provide early warning of ocean acidification extremes and hypoxia events which could devastate vulnerable ecosystems and marine protected areas.

Seasonal forecasts of ocean biogeochemistry are in their infancy, but several studies have already shown potential predictive skill. Tommasi et al. (2017) demonstrated the utility of seasonal forecasts of sea surface temperature (SST) for fisheries management, while downscaling global ocean physics forecasts to create coastal ecosystem forecasts has been demonstrated to aid fisheries management decisions (Siedlecki et al., 2016, 2023; Jacox et al., 2020). Another approach is to combine dynamical ocean models with statistical methods (Matli et al., 2020; Xu et al., 2023), while Jouanno et al. (2023) forced a Sargassum transport-physiology model with ocean-atmosphere seasonal forecasts to generate skilful predictions of Sargassum accumulation in the tropical Atlantic. The approach most akin to state-of-the-art coupled ocean-atmosphere seasonal forecasting systems is to extend these systems to include ocean biogeochemistry, as in Earth System Models (ESMs) used for climate projections. The coupling is typically one-way (ocean biogeochemistry forced by physics either online or offline), but there is scope for two-way coupling (Ford et al., 2018). Séférian et al. (2014) found multi-year predictability for tropical marine productivity, Rousseaux and Gregg (2017) demonstrated skilful seasonal predictions of surface chlorophyll in the tropical Pacific, and extended this to the global ocean in Rousseaux et al. (2021). Park et al. (2019) found chlorophyll prediction skill several months ahead in regions including the tropical Pacific, North Atlantic, and Indian Ocean. Mogen et al. (2023) found forecast skill for temperature, dissolved oxygen, and dissolved inorganic carbon (DIC) across the global ocean, and in a further global study Mogen et al. (2024) found particular skill for marine heatwaves and ocean acidification extremes in the eastern Pacific.

Underpinning seasonal forecasting systems are ocean reanalyses, which combine models and observations through data assimilation to reconstruct the past ocean state. These are often used to initialise and calibrate seasonal predictions, as well as being vital for understanding and quantifying recent climate variability, such as the evolution of the ocean carbon sink which remains highly uncertain (Friedlingstein et al., 2025).

Accurate reanalyses rely on accurate models and observations, and optimal assimilation strategies to best exploit both sources of information, accounting for their relative uncertainties. Assimilation of ocean physics observations is well established, bringing clear improvements to ocean physics reanalysis skill (Storto et al., 2019) and coupled ocean-atmosphere seasonal forecasts (Balmaseda et al., 2024; Thierry et al., 2025). Its benefits for ocean biogeochemistry remain unclear though, with several studies reporting deleterious impacts on reanalyses due to increased vertical mixing (Raghukumar et al., 2015; Park et al., 2018; Gasparin et al., 2021), with uncertain consequences for forecasts, and refined strategies are likely required to maximise its contribution to biogeochemical prediction skill (Park et al., 2019). Assimilation of ocean biogeochemistry observations has been shown to improve the skill of reanalyses and short-range forecasts (Fennel et al., 2019), while a perfect model study suggested that initialising physics variables is more important for multi-year biogeochemistry forecasts (Fransner et al., 2020). For seasonal predictions though, the relative importance of accurately initialising biogeochemical variables versus physics-driven ocean circulation remains an open question. Of the ocean biogeochemical seasonal forecasting efforts discussed above, most only utilised data assimilation as part of the physics forcing datasets, and those that did directly assimilate ocean observations either assimilated only physics (Park et al., 2019) or only biogeochemistry (Rousseaux and Gregg, 2017; Rousseaux et al., 2021).

A key decision is which observations to use, and how to use them. Satellites provide routine and widespread coverage of the ocean surface, and the role of satellite data are focused on in this study. Specifically, satellite data from the European Space Agency (ESA) Climate Change Initiative (CCI) (Plummer et al., 2017; https://climate.esa.int), which provides long-term high-quality climate data records (CDRs) for many essential climate variables (ECVs). Another component of the ESA CCI is its Climate Modelling User Group (CMUG), which aims to bring together the remote sensing and climate modelling communities, and provided the funding for this work.

This study used the ocean reanalysis components of two separate seasonal forecasting systems, run by Barcelona Supercomputing Center (BSC) and Met Office (MO) respectively, to explore the relative impacts of assimilating ocean physics and biogeochemistry satellite data on ocean reanalyses and potential prediction skill, aiming to inform initialisation strategies for seasonal forecasts of global ocean biogeochemistry.

2. Observations

This section details in turn the observation products used for assimilation and validation in this study.

2.1 Satellite data

The satellite data products used are summarised in Table 1, and detailed below.

ECV	Assimilated (BSC)	Assimilated (MO)	Validation only
Ocean colour	BICEP/NCEO monthly L3 phytoplankton carbon derived from OC-CCI v5.0	OC/-CCI v6.0 daily L3 chlorophyll	BICEP/NCEO monthly L3 primary production derived from OC-CCI v4.2
Sea ice		OSI SAF OSI-450-a (v3.0) daily L4 SIC	
Sea level		CMEMS along-track L3 sea level anomaly	
SST	SST-CCI v3.0 daily L4	SST-CCI v3.0 along-track L2P/L3U	
SSS		SSS-CCI v4.41 along-track L2P	
Ocean carbon			UExP-FNN-U (v2026-pre1)

Table 1: Satellite data products used in this study. See following sections for details.

2.1.1 Ocean colour

The ocean colour CCI project (OC-CCI) provides daily, 8-day, and monthly level 3 (L3) merged products for water-leaving radiances, inherent optical properties, and derived chlorophyll (Sathyendranath et al., 2019). The latest version is v6.0 (Sathyendranath et al., 2023), and daily chlorophyll products from v6.0 were used in MO assimilation experiments.

Further products can be derived from ocean colour data, and the PHYTO-CCI project (https://climate.esa.int/en/projects/PHYTO-CCI/) will add many of these to the CCI catalogue in future. As a precursor to this, the ESA Biological Pump and Carbon Exchange Processes (BICEP) project, with support from the National Centre for Earth Observation (NCEO), derived products including phytoplankton carbon (PhyC) and primary production from OC-CCI data.

For BSC assimilation experiments we used monthly L3 phytoplankton carbon derived from OC-CCI v5.0 (Sathyendranath et al., 2020, 2021). This product provides the total carbon concentration of phytoplankton as well as the concentration of the pico-, nano- and microphytoplankton size classes. The algorithm is based on a coupled model of primary production and photoacclimation in the surface mixed layer of the ocean. Data were generated at monthly temporal and 4 km spatial resolution between 1998 and 2022. For both modelling systems, monthly L3 primary production derived from OC-CCI v4.2 (Kulk et al., 2020, 2021) was used for validation in addition to the assimilated data.

2.1.2 Sea ice concentration (SIC)

The sea ice CCI project provides sea ice concentration (SIC) and sea ice thickness (SIT) CDRs. SIC developments are coordinated with the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Ocean and Sea Ice Satellite Application Facility (OSI SAF), and the OSI-450-a (v3.0) CDR from OSI SAF (EUMETSAT OSI SAF, 2022) was used in MO assimilation experiments.

2.1.3 Sea level anomaly (SLA)

The sea level CCI project has produced a global CDR from 1993-2015, and is now developing coastal altimetry products (Cazenave et al., 2022). Operational production of global products has shifted to the Copernicus Climate Change Service (C3S) and Copernicus Marine Service (CMEMS), and MO assimilation experiments used the CMEMS product SEALEVEL_GLO_PHY_L3_MY_008_062 (https://doi.org/10.48670/moi-00146) which provides along-track L3 sea level anomaly (SLA).

2.1.4 Sea surface salinity (SSS)

The sea surface salinity (SSS) CCI project uses satellite observations available since 2010 to produce weekly and monthly gridded SSS products (Boutin et al., 2021). While not publicly available, along-track L2P SSS is produced as part of the processing chain, and made available to researchers on request. L2P SSS from v4.41 was used in MO assimilation experiments.

2.1.5 Sea surface temperature (SST)

The SST CCI project (SST-CCI) produces CDRs from three series of thermal infra-red sensors: the Advanced Very High Resolution Radiometers (AVHRRs), the Along-Track Scanning Radiometers (ATSRs), and the Sea and Land Surface Temperature Radiometers (SLSTRs); and two microwave sensors: the Advanced Microwave Scanning Radiometers (AMSR), giving a record from 1980 (Embury et al., 2024). MO assimilation experiments used the v3.0 along-track L2P/L3U products (Embury, 2024a,b), while BSC assimilation experiments used the L4 gap-free daily products (Good and Embury, 2024).

2.1.6 Ocean carbon

The ESA CCI project Ocean Carbon for Climate (OC4C) (https://climate.esa.int/en/supporting-the-paris-agreement/ocean-carbon-4-climate/) aims to produce CDRs of ocean carbon variables using multiple satellite ECV data as input. As a precursor to this, the ESA OceanSODA project generated an initial set of these products. In this study, the OceanSODA-ETHZ v5.5 (Gregor and Gruber, 2020, 2021) monthly L4 pCO_2 and pH data were used for validation. An initial development from OC4C, the UExP-FNN-U (v2026-pre1) dataset (Daniel Ford and Jamie Shutler, personal communication) was also used for pH.

2.2 In situ data

While the focus of this study is on the role of satellite data, both systems also assimilated in situ physics data as this forms a standard part of the existing reanalysis systems and is key in terms of physics reanalysis and forecast skill (Balmaseda et al., 2024; Thierry et al., 2025). In situ biogeochemistry data can be assimilated (While et al., 2012; Ford, 2021), but this is not yet done routinely, so has just been used for validation in this study. The in-situ datasets used for assimilation and validation are described in turn below.

2.2.1 Temperature and salinity (T&S)

The Met Office Hadley Centre EN4 dataset (Good et al., 2013) provides quality-controlled profiles of temperature and salinity (T&S), as well as monthly gap-filled objective analyses from 1900. MO assimilation experiments used temperature and salinity profiles from EN4.2.2 with Gouretski and Reseghetti (2010) corrections. BSC used the monthly T&S analyses from the same version.

MO experiments additionally assimilated in situ SST observations from the Hadley Centre Integrated Ocean Database (HadIOD) (Atkinson et al., 2014).

2.2.2 Biogeochemistry

For validation purposes, monthly climatological fields of nitrate from the World Ocean Atlas 2023 (WOA23) climatology were used, which is based on historic in situ observations (Garcia et al., 2023).

3. Modelling systems

3.1 BSC

The experiments carried out at the BSC used the ocean component of the Earth System Model (ESM) EC-Earth (Döscher et al., 2022). This configuration consists of the NEMO ocean general circulation model version 4.2 (Madec and the NEMO System Team, 2023) with an ORCA1 grid (~ 1° horizontal resolution), coupled with the PISCESv2 biogeochemical model (Aumont et al., 2015), a model of intermediate complexity designed for global ocean biogeochemical applications. It includes 24 prognostic variables and simulates biogeochemical cycles of oxygen, carbon and the primary nutrients controlling phytoplankton growth (nitrate, ammonium, phosphate, silicic acid and iron).

PISCESv2 distinguishes four plankton functional types based on size: two phytoplankton groups (small = nanophytoplankton and large = diatoms) and two zooplankton groups (small = microzooplankton and large = mesozooplankton). For phytoplankton, the prognostic variables include total biomass in C, Fe, Si (for diatoms) and chlorophyll, making the Fe/C, Si/C, Chl/C ratios variable. In contrast, for zooplankton, these ratios are constant, with total biomass in C being the only prognostic variable. The bacterial pool is not explicitly modelled. The model also distinguishes three non-living pools for organic carbon: small particulate organic carbon, large particulate organic carbon and semi-labile dissolved organic carbon. Additionally, alongside the three organic detrital pools, carbonate and biogenic siliceous particles are modelled. The model is also capable of resolving the carbonate system, incorporating variables such as dissolved inorganic carbon and total alkalinity.

Data assimilation is performed using a nudging scheme, which applies a bias towards observations at each model timestep. The strength of the bias depends on the difference between the observed and the modelled value at a particular timestep, and a restoring factor set to 30 days for this study, as described further in Section 4.1.

3.2 Met Office

MO employs a seamless modelling strategy across weather and climate time scales (Brown et al., 2012), with the same models used for short-range ocean forecasting with the Forecast Ocean Assimilation Model (FOAM) (Mignac et al., 2025), atmosphere-ocean seasonal forecasting with GloSea (Kettleborough et al., 2026), and Earth system climate modelling with the UK Earth System Model (UKESM) (Mulcahy et al., 2023).

The current generation of systems is based around the Global Coupled model version 5 (GC5) configuration (Xavier et al., 2023). For ocean physics and sea ice this uses the UK Global Ocean and Sea Ice configuration version 9 (GOSI9) (Guiavarc'h et al., 2025), based on v4.0.4 of the NEMO ocean modelling framework (Madec and NEMO system team, 2019) and the SI^3 sea ice component (Blockley et al., 2024). For ocean biogeochemistry, version 2.1 of the Model of Ecosystem Dynamics, nutrient Utilisation, Sequestration and Acidification (MEDUSA) (Yool et al., 2013, 2021) is used. In global ocean configurations, biogeochemistry is currently only routinely included as part of UKESM (Mulcahy et al., 2023), but has been used for research purposes coupled with the FOAM reanalysis system (Ford, 2020, 2021). Ocean data assimilation is performed using NEMOVAR (Waters et al., 2015; Mirouze et al., 2016).

The ocean physics and sea ice model setup used in this study was the same as the 1/4° resolution configuration presented in Mignac et al. (2025), although in this study atmospheric forcing was provided by the ECMWF ERA5 reanalysis (Hersbach et al., 2020). The MEDUSA version of Yool et al. (2021) was coupled as described in Ford (2021); the coupling was one-way with no feedback from biogeochemistry to physics.

Data assimilation of SST, SLA, SIC, and T&S profiles – the standard variables currently assimilated in FOAM and in the ocean reanalysis used with GloSea – was as described in Mignac et al. (2025). This used a first guess at appropriate time (FGAT) 3D-Var configuration of NEMOVAR (specifically NEMOVAR v6.5.26 in this study).

Assimilation of SSS data are not yet operational, but has been developed (Martin et al., 2019, 2022). The method used in this study was as described in Martin et al. (2019). Due to high observation uncertainties at higher latitudes, SSS observations were only assimilated between 40°N and 40°S.

Assimilation of OC-CCI chlorophyll data was tested in two different configurations in this study. The first used the method described in Ford (2021). In this, NEMOVAR was used to calculate a set of increments to total surface $\log_{10}$(chlorophyll) on the model grid. For application to MEDUSA, which models phytoplankton biomass and chlorophyll using two phytoplankton functional types (PFTs) (Yool et al., 2013), the total chlorophyll increments were split into increments to each PFT chlorophyll variable in such a way as to maintain the background model ratio between the PFTs at each grid point. Similarly, increments to the PFT biomass variables were calculated to maintain the background carbon to chlorophyll ratio (and silicon to chlorophyll ratio for diatoms) for each PFT. These increments were applied throughout the model mixed layer.

The second configuration also used NEMOVAR to calculate increments to total surface $\log_{10}$(chlorophyll), but then calculated increments to a wider array of model state variables throughout the water column using the nitrogen balancing scheme of Hemmings et al. (2008). The concept of the scheme is to determine whether phytoplankton errors at each grid point are primarily the result of growth errors or loss errors, and calculate increments to the wider model state variables accordingly while conserving mass. The scheme was designed for the simpler Hadley Centre Ocean Carbon Cycle model (HadOCC) (Palmer and Totterdell, 2001), which models one class each of phytoplankton and zooplankton, compared with the two classes of each modelled by MEDUSA. The implementation for global studies with HadOCC of Ford et al. (2012) was extended here to MEDUSA in a way that preserved the internal workings of the scheme described in Hemmings et al. (2008). The MEDUSA phytoplankton and zooplankton variables were summed at each grid point, and these were passed to the nitrogen balancing code along with the MEDUSA dissolved inorganic nitrogen (DIN), detrital nitrogen, DIC, and alkalinity variables (equivalent to the six state variables of HadOCC). The increments calculated to these latter four were applied directly to those model variables, while increments to the two PFTs and zooplankton types were split in a way that preserved their background ratios, as in the first configuration. Additionally, diatom silicon was updated to preserve its ratio to diatom nitrogen, and silicate updated equally and oppositely to conserve mass. Finally, detrital carbon was updated to preserve its ratio to detrital nitrogen. This method has the advantage of maintaining the functionality and principles of the Hemmings et al. (2008) scheme, but the disadvantage that the code still uses parameterisations designed for HadOCC rather than MEDUSA; updating this would be a major piece of work outside the scope of this study.

For stability reasons, in both cases biogeochemical balancing increments were limited in certain areas, similar to Ford (2020). No biogeochemical increments were applied in grid boxes with SIC > 0.01, in the Indonesian Throughflow region where there is special treatment of tidal mixing (Koch-Larrouy et al., 2008), or in grid boxes where any of the phytoplankton state variables were ≤ 0.0. In shelf seas (model bathymetry ≤ 250 m) only chlorophyll increments were applied, with no further balancing. At all grid points, the maximum total absolute chlorophyll increment was capped at 2.0 mg m^{-3}, enforced prior to the balancing scheme being run, and the mixed layer depth (MLD) used by the balancing was capped at 250 m.

4. Experiments

This section describes the reanalysis experiments performed with the two systems. There was deliberately no attempt to harmonise the experiments run between the two systems or their initialisation or inputs. Experimental configurations were chosen which make sense for how each system is run (or would be run) operationally, to provide a real-world test of the impact of different observation products and assimilation choices. For reasons of computational expense due to the different model resolutions, the MO experiments were run for a shorter period than the BSC experiments, though these periods overlapped. Each experiment was assessed and validated against observation-based data to provide system-dependent conclusions, with these then compared to provide more general conclusions.

4.1 BSC

The BSC first spun the model up to a quasi-equilibrium state by running five repeated cycles of the 1959–2021 period forced by ERA5 reanalysis atmospheric cycles in preindustrial conditions (Griffies, 2016; Bernardello et al., 2022). This was then used to initialise a set of assimilation experiments (Table 2). For all experiments, subsurface temperature and salinity were nudged towards the EN4 subsurface ocean dataset (Good et al., 2013). As detailed below, the differences between experiments lay on the different satellite ECV products used to nudge surface variables.

CONTROL: The first experiment is an ocean reconstruction in which we only nudged temperature and salinity in the ocean subsurface using EN4.

SST_CCI: In this experiment, branching off from the CONTROL and covering the period 1980-2021, we nudged sea surface temperature (SST) with the SST-CCI v3.0 daily L4 product and sea surface salinity (SSS) from ECMWF’s ORAS5 reanalysis (Zuo et al., 2019), which was used instead of the ESA SSS-CCI product due to its availability for a much longer period.

SST_CCI+PhyC: This experiment presents the same physical data assimilation setup as SST_CCI but incorporates assimilation of the CCI-derived phytoplankton carbon (PhyC) product (Sathyendranath et al., 2020). It also branches off from the CONTROL and covers the period 1998-2021, for which PhyC observations are available. The PhyC product estimates the phytoplankton carbon contribution of three phytoplankton groups, yet the biogeochemical model PISCESv2 represents two groups. This mismatch was overcome by amalgamating the two groups in PhyC representing large-celled phytoplankton, and assimilating this into the PISCESv2 macro-phytoplankton group.

Experiment name	Profile T&S assimilated	SST assimilated	Ocean colour assimilated
CONTROL			
SST_CCI			
SST_CCI+PhyC			

Table 2: Overview of BSC experiments.

The BSC set of experiments was run to test the hypothesis that satellite-derived biogeochemical variables can be used to improve biogeochemical models. The method we used to test this idea, called "nudging", applies a bias towards observations at each model timestep. The strength of the bias depends on the difference between the observed and the modelled value at a particular timestep, and a restoring factor set to 30 days for this study. The phytoplankton carbon product was chosen as the best candidate variable to test the hypothesis because carbon is the fundamental currency in PISCESv2. Chlorophyll was decided against as it is a secondary variable in the model, resulting from flexible ratios, hence more likely to damp down the effectiveness of the nudging.

4.2 Met Office

All MO experiments started from the same initial conditions. Given the known positive impact of physics assimilation on the ocean circulation (Mignac et al., 2025), it would seem desirable to use a previous physics assimilation run to provide the most realistic physics initial conditions. Conflicting with this though, is the known impact of physics assimilation on vertical mixing, which can degrade biogeochemistry (Ford, 2020). To try and best satisfy both these considerations, physics and sea ice initial conditions for 1 July 2015 were taken from the most recent GloSea ocean physics reanalysis assimilating SST, SIC, SLA, and T&S (Tamara Collier and Richard Renshaw, personal communication), and the model then run forward with no data assimilation. After three months, by which time the vertical velocities had returned to free run levels, biogeochemistry was coupled using initial conditions from a previous free run. This was run on for a further three months with no data assimilation to provide the initial conditions for the experiments presented here.

Six experiments were performed with the MO system, as summarised in Table 3. Each experiment was run for five years from 1 January 2016 to 31 December 2020. Ideally, reanalyses in support of seasonal forecasting would cover a longer period, but running multiple reanalyses at 1/4° resolution with coupled biogeochemistry is computationally expensive and this was unfeasible within the scope of this study. Five years is sufficient to draw robust conclusions about the impact of data assimilation, and any future operational system would use a longer reanalysis.

FREE was a model free run with no data assimilation. **STANDARD** assimilated the same variables as the current operational physics systems and GloSea reanalysis (SST, SIC, SLA, T&S); the impact on biogeochemistry of assimilating each of these variables in isolation was previously explored by Ford (2020). **STANDARD+SSS** added assimilation of SSS data, while **SSS** assimilated SSS on its own; this latter would not be done operationally, but was run to isolate its impact on biogeochemistry which has not previously been looked at. Two experiments, **STANDARD+SSS+OC** and **STANDARD+SSS+OCbal**, added assimilation of chlorophyll from ocean colour to the full set of physics observations, using Ford (2021) and Hemmings et al. (2008) balancing respectively. The run **STANDARD+SSS+OCbal** crashed due to an error in October 2019, so results shown for this run are incomplete.

As well as the physics and biogeochemistry model variables, each run included a standalone passive tracer, initialised to be equal to the MEDUSA DIN initial conditions, which was advected and diffused but did not interact with the biogeochemistry. This was to help isolate the role of physics changes on the transport of biogeochemical fields.

Experiment name	Profile T&S assimilated	SST, SIC, SLA assimilated	SSS assimilated	Ocean colour assimilated
FREE				
SSS			✓	
STANDARD	✓	✓		
STANDARD+SSS	✓	✓		
STANDARD+SSS+OC	✓	✓	✓	Ford (2021) balancing
STANDARD+SSS+OCbal	✓	✓	✓	Hemmings et al. (2008) balancing

Table 3: Overview of MO experiments.

5. Results

Section 5.1 focuses on primary production, being the biogeochemical variable of most interest for fisheries management, with each of the two systems considered in turn. Section 5.2 then assesses the wider model state in the MO system, which is the one that will be used in follow-on seasonal forecasting experiments, focusing on variables and processes expected to be most relevant for seasonal prediction skill.

5.1 Primary production

5.1.1 BSC

To evaluate the influence of nudging to the modelled primary production we compare the **SST_CCI** experiment with **SST_CCI+PhyC**.

SST_CCI shows that nudging towards SST induced colder waters in the Gulf Stream, along the western coasts of South America and Africa and the North Pacific (Fig. 1). Subtropical gyres were generally weakly warmer (<2°C) after nudging and the Southern Ocean presented mixed warmer/colder patterns along the Antarctic Circumpolar Current, with predominance of colder waters. **SST_CCI+PhyC** shows almost no difference in SST with respect to **SST_CCI**. This result was expected as the nudging of surface phytoplankton can only influence SST through an indirect effect of heat absorption by phytoplankton cells (Brewin et al, 2019).

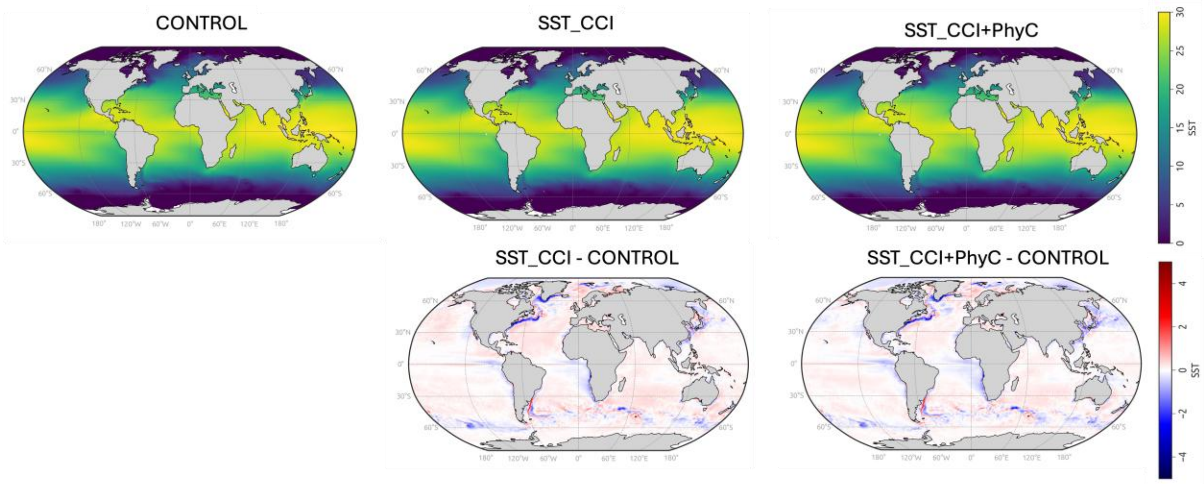

Figure 1: 20-year mean sea surface temperature (2000-2019) in **SST_CCI** and **SST_CCI+PhyC** compared to **CONTROL**.

In contrast, the two experiments show differences in the modelled water column-integrated primary production (intPP) (Fig. 2), which are particularly notable in the Tropics. While nudging only SST induced an increase in productivity in the Equatorial Pacific and a decrease in the North Pacific, the experiment with additional nudging of PhyC presents more marked and complex patterns. For instance, the productivity increase in the Equatorial Pacific persists but appears limited to the eastern part of the basin, with decreases in the subtropical regions. A reduction in intPP is also modelled in the Indian Ocean, while the Equatorial and Southeast Atlantic present a clear increase in productivity. Differences are also evident in the North Pacific sector, where **SST_CCI** shows a stronger productivity decrease than **SST_CCI+PhyC**. In the North Atlantic, Southern Ocean and Arctic both experiments show very similar results, with productivity increases in the first two areas, and productivity decreases in the latter.

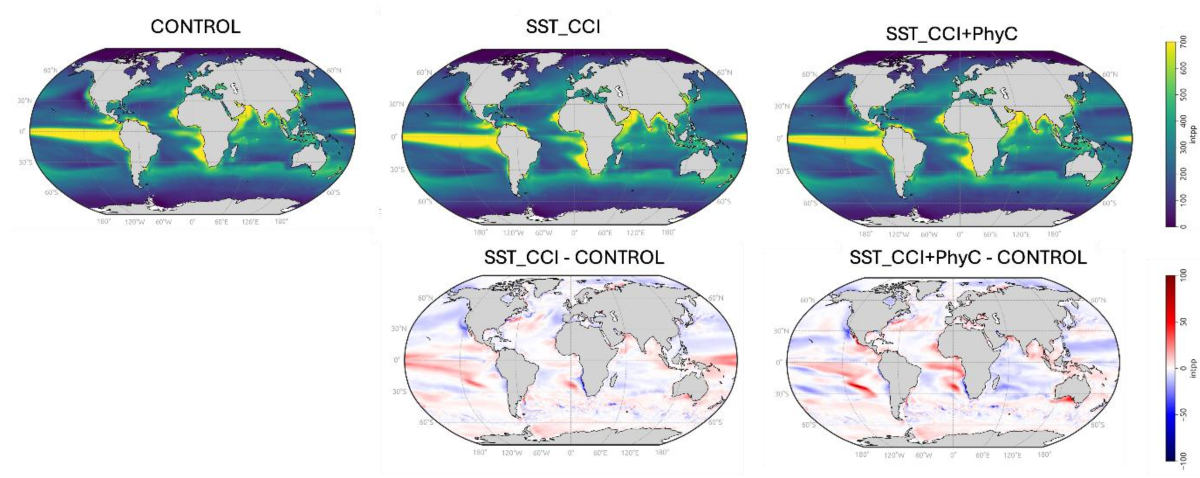

Figure 2: 20-year mean integrated primary production (2000-2019) in **SST_CCI** and **SST_CCI+PhyC** compared to **CONTROL**.

The changes induced by nudging SST and PhyC are one order of magnitude smaller than the differences between the modelled and the satellite-estimated intPP, as demonstrated by a time series of each in the Equatorial Pacific (Fig. 3), a region where previous studies have found predictive skill (Séférian et al., 2014; Rousseaux and Gregg, 2017). Neither of the two nudging techniques improved the model skill compared with the observation-based product. The reasons for this are likely the complex and interdependent parameter space in PISCESv2 which make the model inflexible to "external" perturbations.

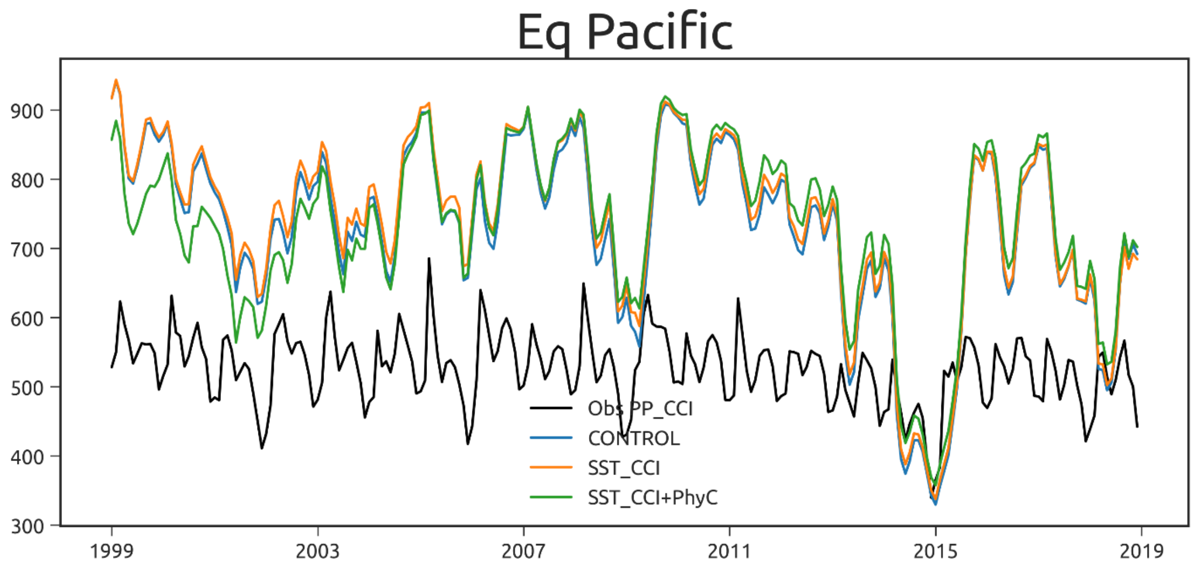

Figure 3: 20-year integrated primary production timeseries over the Equatorial Pacific (-5, 5, 180,270) for the three BSC model simulations and the observation-based dataset.

5.1.2 Met Office

Assessment of the assimilation of SST and chlorophyll in an older version of the MO system was presented in Ford (2020), and this section focuses on the novel aspects in this study. Compared with the assimilated OC-CCI chlorophyll data, each iteration of the assimilation reduced the global root mean squared error (RMSE) of the model background (i.e., prior to assimilation each cycle, essentially a one-day forecast). The largest RMSE was seen in **FREE**, reduced in **SSS**, reduced further in **STANDARD** and **STANDARD+SSS**, and was smallest in the two runs assimilating the OC-CCI data (Fig. 4). Counter to expectations, the more complex balancing scheme of Hemmings et al. (2008) increased the RMSE compared with the simpler balancing method used in Ford (2021).

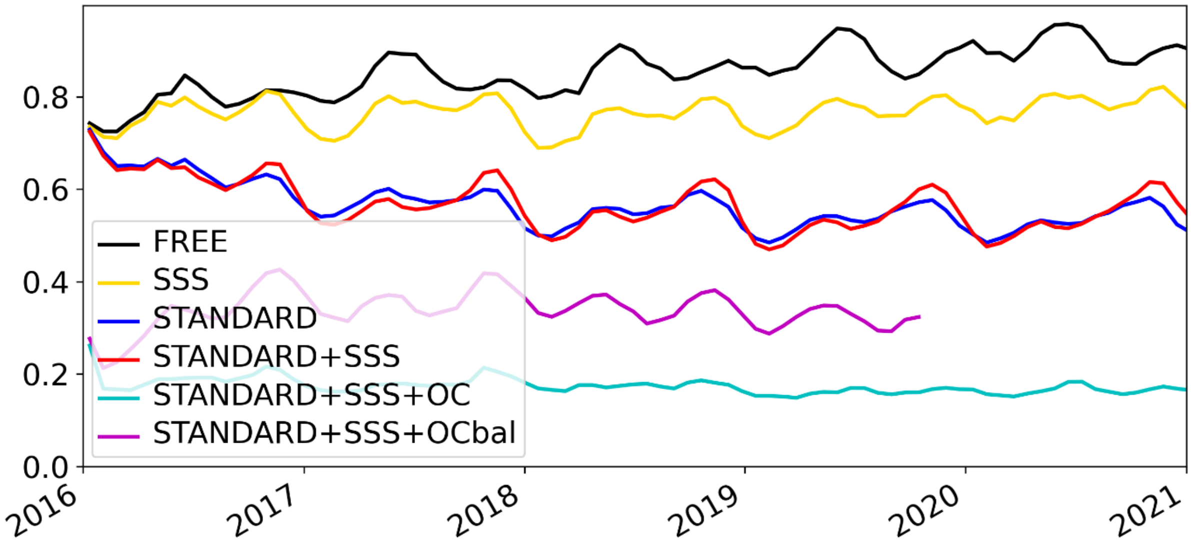

Figure 4: Time series of global background minus observation RMSE of $\log_{10}$(chlorophyll) ($\log_{10}$(mg m^{-3})) from each MO run against the CCI chlorophyll observations.

Looking at maps of intPP for each run for June 2019 (northern hemisphere spring/summer in the final year with results from all runs) compared with the satellite-based product (Fig. 5), the different ECVs have different spatial influences when assimilated. **FREE** matches the broad patterns of the observation-based product, but underestimates intPP in the subtropical gyres. **SSS** improves this to some extent, with its biggest changes seen at mid-latitudes. **STANDARD** results in higher intPP globally, but especially around the equator, while **STANDARD+SSS** combines these two patterns. Compared with **STANDARD+SSS**, **STANDARD+SSS+OC** increases intPP in the subtropical gyres and decreases it elsewhere, giving the best match for the observation-based product. **STANDARD+SSS+OCbal** generally results in higher intPP. The drivers behind these changes are investigated further in Section 5.2.

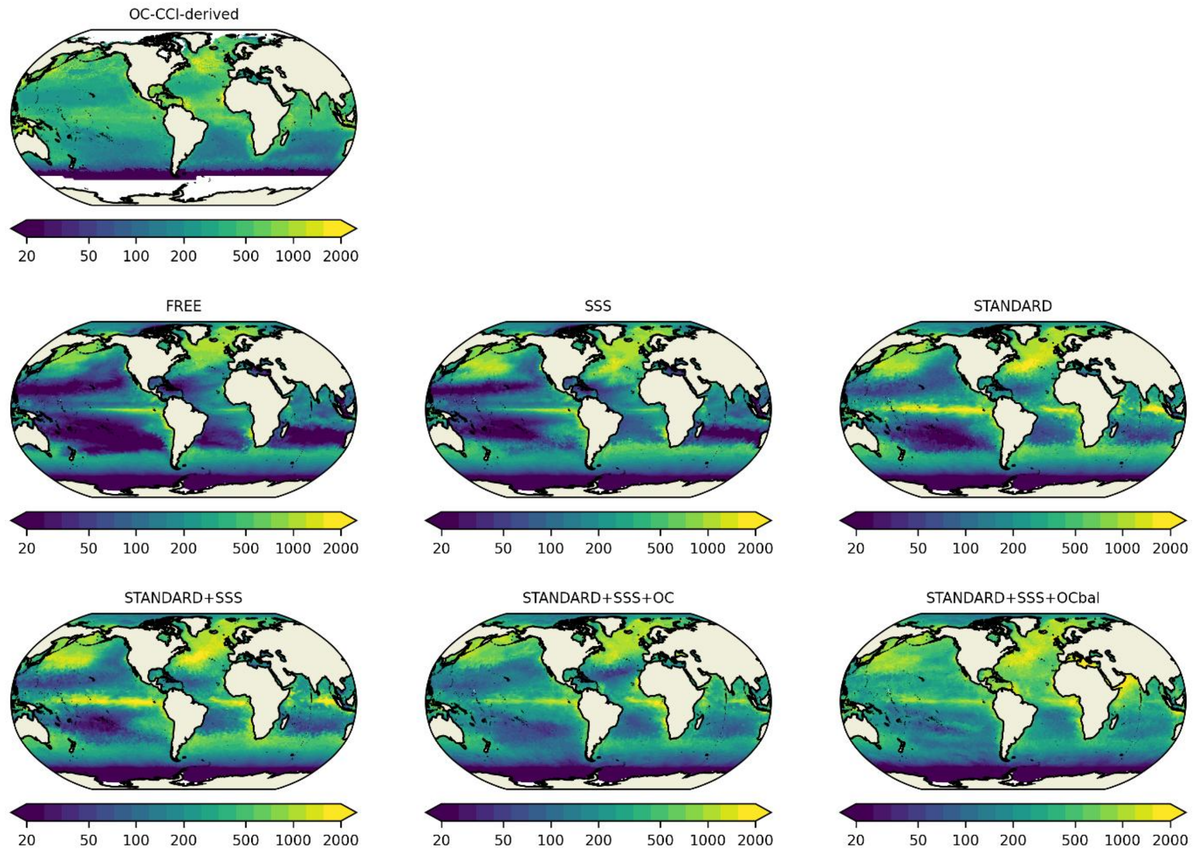

Figure 5: Monthly mean column-integrated primary production for June 2019 from each MO run and the BICEP product derived from OC-CCI data.

5.2 Wider model state

This section looks at the wider physics and biogeochemistry model state in the MO experiments, to help explain the results seen in Section 5.1.2, and further investigate potential seasonal prediction skill with different assimilation choices. The figures focus on the same month as Fig. 5, but the conclusions are more broadly representative.

Figure 6 shows the turbocline depth (the measure of mixed layer depth used by biogeochemistry within NEMO) for June 2019 of each distinct physics run, and their difference to their relative control (**FREE** for **SSS** and **STANDARD**, and **STANDARD** for **STANDARD+SSS**). Assimilating SSS deepens the turbocline depth across much of the Pacific and at around 40°S, the limit at which the observations are assimilated (see Section 3.2). This appears to be one of the main mechanisms for SSS impact on biogeochemistry, with a similar effect seen in the northern hemisphere in other months (not shown). Assimilating only SSS data degrades subsurface salinity compared with EN4 data (not shown), which is not the case in **STANDARD+SSS**, demonstrating the role of SSS data as part of a multivariate assimilation system. Interestingly, in **STANDARD** there is a shallowing of the turbocline depth in the chaotic region east of the Agulhas current, where **SSS** shows a deepening. Elsewhere, **STANDARD** has a mixed impact on the turbocline depth, but most commonly deepens it; this is not enough to explain the changes in intPP in **STANDARD** seen in Fig. 5 though.

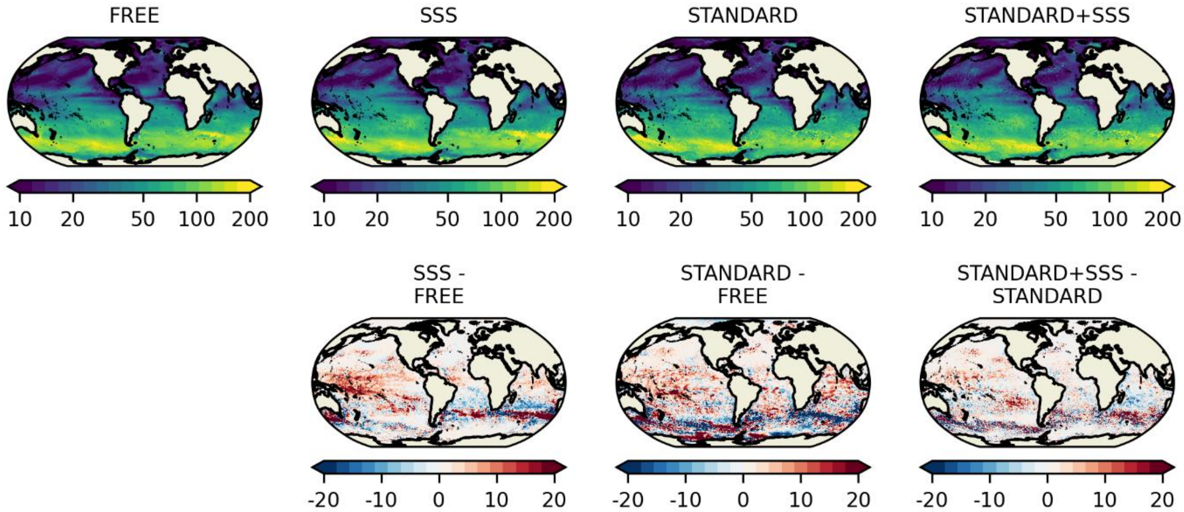

Figure 6: Monthly mean turbocline depth (m) for June 2019 from each distinct physics setup, and their difference to their relative control.

The combination of variables assimilated in **STANDARD** has previously been noted to result in increased vertical mixing around the equator (Ford, 2020) which upwells excessive carbon and nutrients and impacts primary production. A sizeable increase in the magnitude of vertical velocities remains evident in **STANDARD** (Fig. 7), although recent developments to the bias pressure correction (Barbosa Aguiar et al., 2024) and temperature correlation length scales (Mignac et al., 2025) may have helped mitigate this. The addition of SSS assimilation has some impact (Fig. 7), but mostly on the chaotic patterns rather than the absolute magnitudes.

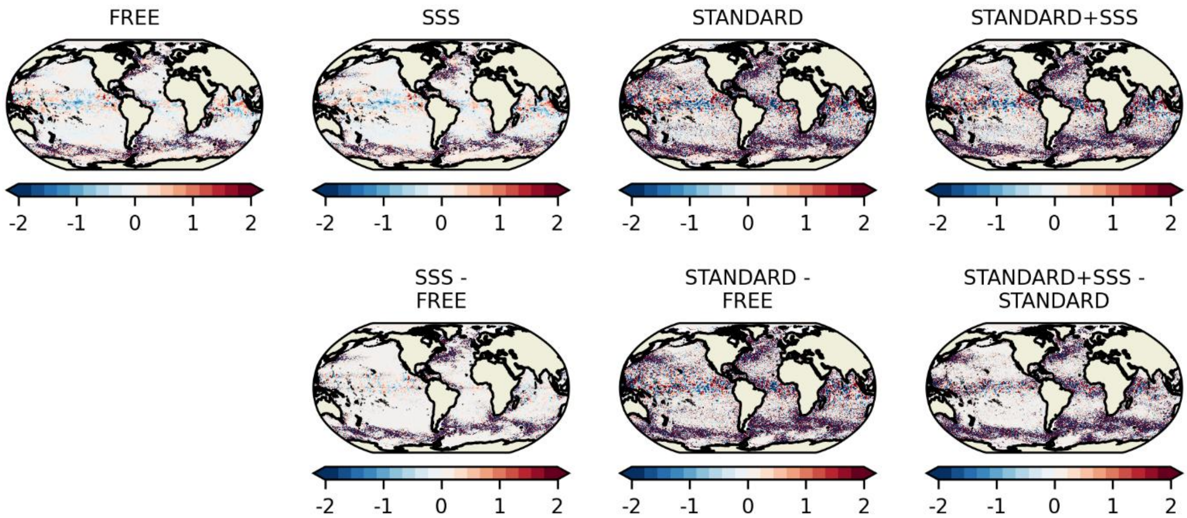

Figure 7: Monthly mean vertical velocity (m d^{-1}) at 500 m depth for June 2019 from each distinct physics setup, and their difference to their relative control.

The impact of this change in vertical mixing on biogeochemical fields is demonstrated in Fig. 8, which shows maps of the surface concentration of a standalone passive tracer which was initialised from the DIN field and subject only to physical processes (see Section 3.2).

Consistent with findings from multiple centres (Park et al., 2018; Ford, 2020; Gasparin et al., 2021), **STANDARD** results in much higher surface concentrations, especially at low latitudes, than in **FREE**. Adding SSS to **STANDARD** makes minimal difference to passive tracer concentrations, but compared with **FREE**, **SSS** shows higher concentrations at mid-latitudes. In each case, these can be linked to the patterns of intPP changes seen in Fig. 5.

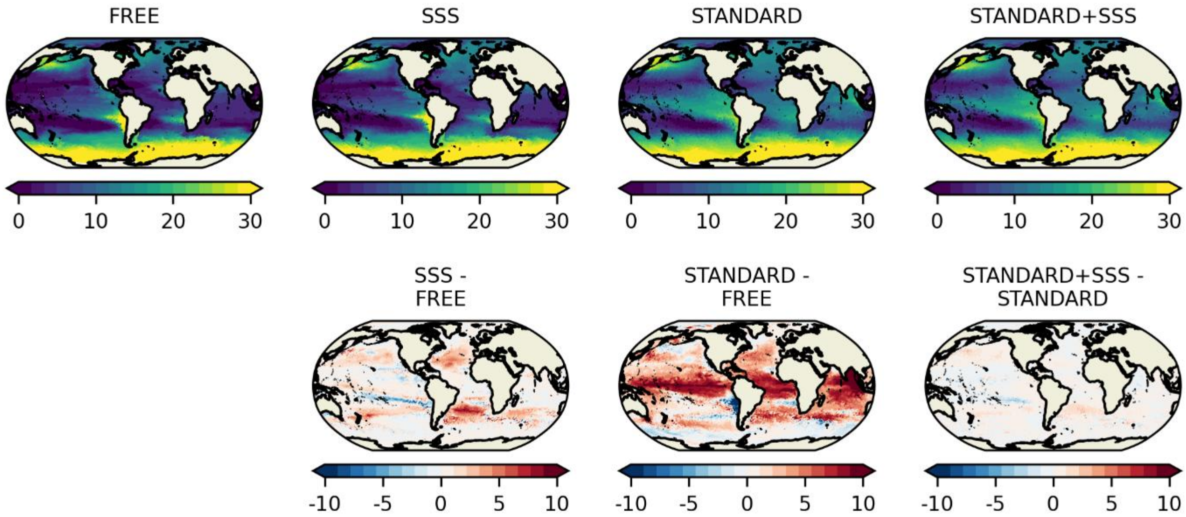

Figure 8: Monthly mean standalone passive tracer concentration (originally mmol N m^{-3}) at the surface for June 2019 from each distinct physics setup, and their difference to their relative control.

The corresponding fields of surface DIN, which is subject to biogeochemical as well as physical processes, are shown in Fig. 9, and compared to the WOA23 climatology. The changes in DIN due to physics assimilation are comparable, but not as pronounced, demonstrating complex biogeochemical feedbacks. The increased upwelling around the equator results in a better match for the observation-based climatology, though whether this is correcting or cancelling an error needs further investigation. Adding assimilation of chlorophyll with limited multivariate balancing (**STANDARD+SSS+OC**) has a small impact, mostly slightly reducing surface nutrient concentrations. The run with more complex multivariate balancing (**STANDARD+SSS+OCbal**) has a much larger impact on DIN though, as a result of the direct updates made to the nutrient fields, increasing surface DIN globally. In some regions this results in a better match for the WOA23 climatology, but overall it represents a degradation in skill. Analysis (not shown) suggests that this has primarily come about due to a model chlorophyll bias that the assimilation is continually trying to correct in the same direction, resulting in an imbalance in the nutrient increments applied. This demonstrates the potential for multivariate balancing to make widespread changes to the model, but also the importance of correctly formulating such schemes and ensuring assumptions (unbiased models and observations are assumed by most assimilation schemes) are met.

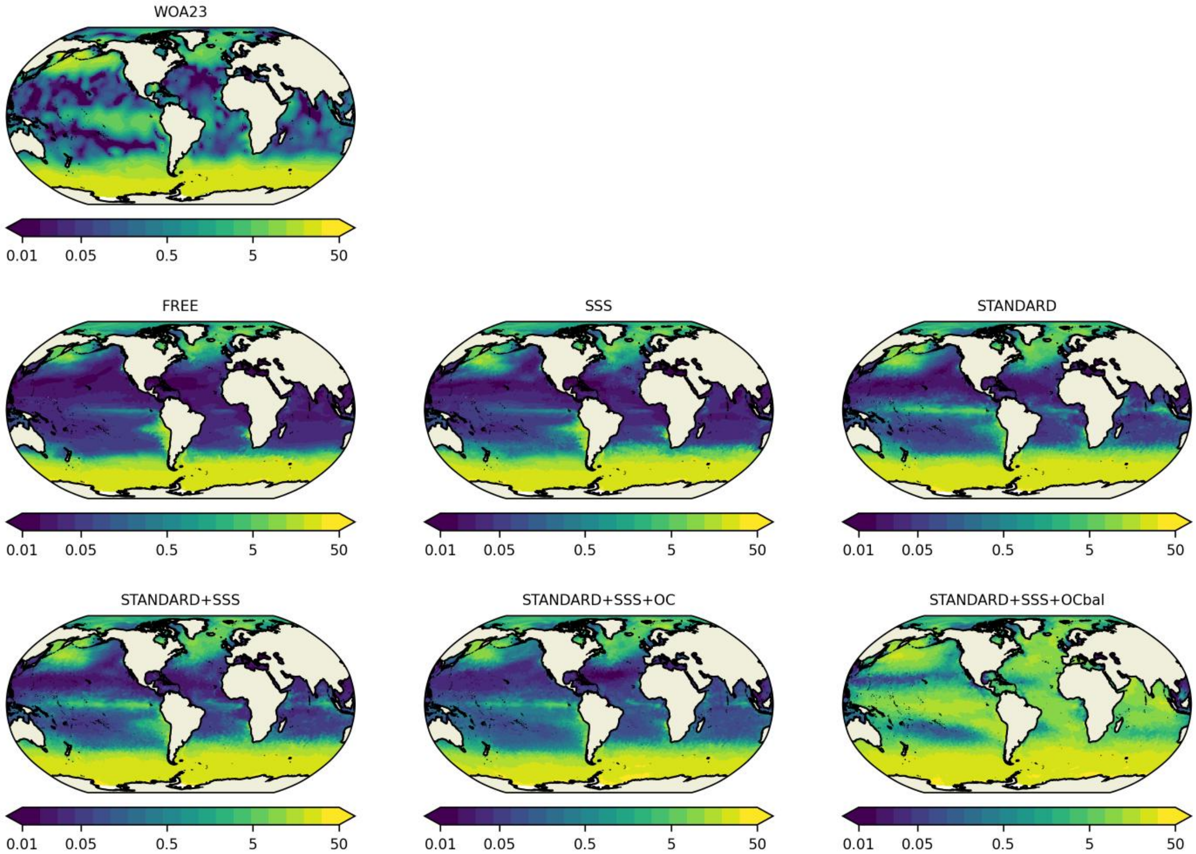

Figure 9: Monthly mean surface nitrate (mmol N m^{-3}) for June 2019 from each run, and the climatology from World Ocean Atlas (WOA23).

Similar maps of surface pCO_2 and pH, this time compared with the OceanSODA-ETHZ product, are shown in Fig. 10 and Fig. 11 respectively. For pH, the UExP-FNN-U (v2026-pre1) product, which builds on OceanSODA-ETHZ and OC4C developments, is also shown. The patterns of impact in each case are broadly the same as for DIN, indicating a common impact on biogeochemistry from the physics assimilation, and whole-model impact of the Hemmings et al. (2008) multivariate balancing used in **STANDARD+SSS+OCbal**. The direct impact on carbonate chemistry from assimilating SSS appears small, indicating its role in affecting ocean mixing to be of higher order.

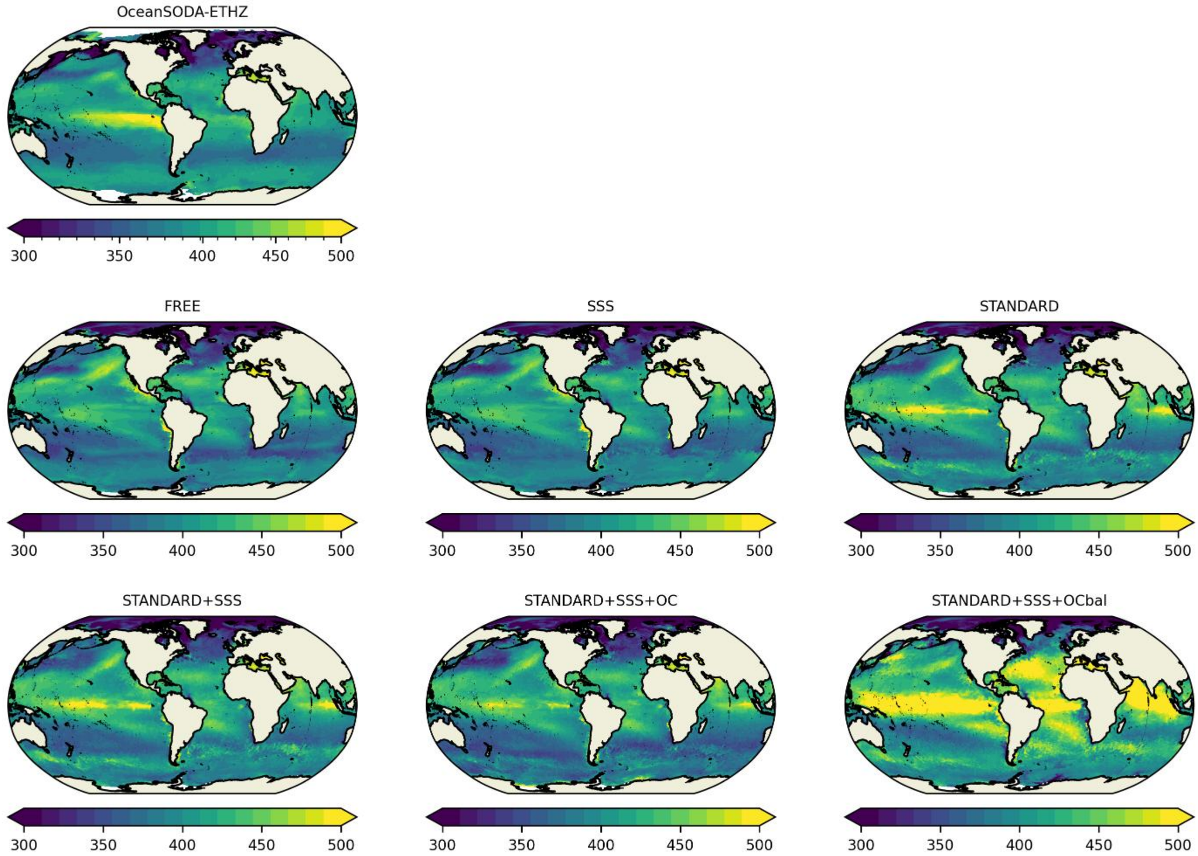

Figure 10: Monthly mean surface pCO_2 for June 2019 from each run and the OceanSODA-ETHZ observation-based product.

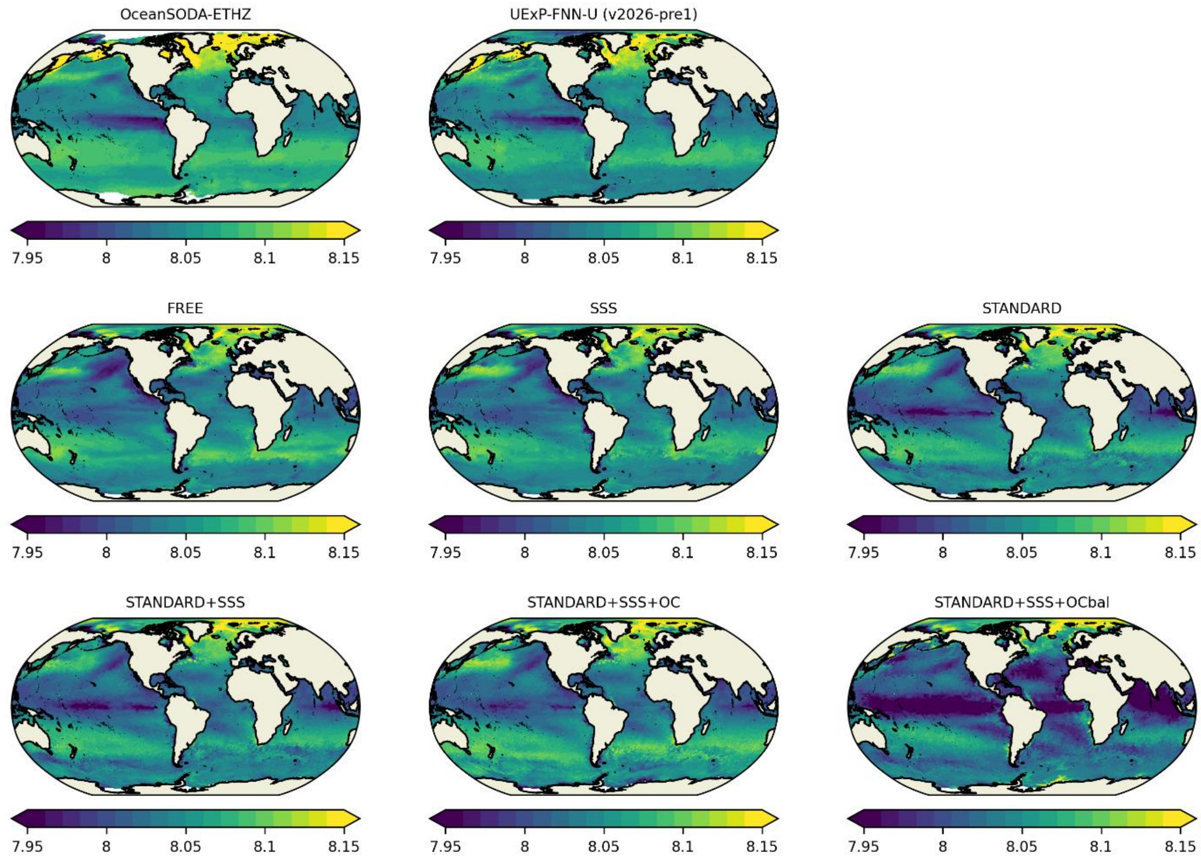

Figure 11: Monthly mean surface pH for September 2019 from each run and the OceanSODA-ETHZ and UExP-FNN-U (v2026-pre1) observation-based products.

6. Summary and conclusions

This study used two separate global ocean physical-biogeochemical reanalysis systems to assess the impact of different assimilation configurations and satellite observation products on properties relevant to seasonal forecasting of global ocean biogeochemistry.

Experiments run by the Barcelona Supercomputing Center (BSC) tested the hypothesis that state-of-the-art satellite-based products can improve model predictions. One experiment used sea surface temperature (SST) from the ESA Climate Change Initiative (CCI) to nudge the model, and a second experiment used both SST-CCI and phytoplankton carbon (PhyC) derived from CCI ocean colour data. Both experiments showed that the nudging influenced the modelled SST and primary production, particularly in the Equatorial Pacific. Yet, the absolute value of this influence was, on average, lower than 10%, when often the model is biased more than 100% when compared to observation-based estimates of primary production. Nudged model outputs were not successful in improving the observed monthly variability. These results suggest that nudging SST and PhyC CCI products was insufficient to significantly improve the model simulations. The cause of the low model flexibility is associated with the model architecture and design, highly parametrised and tuned to reproduce consistent global trends. However, the nudged mechanism was successful technically, proving its potential application with other observed datasets or restoring constants. A future line of research is the application of satellite-based datasets to infer flexible parametrisations that tune the model towards observations, in a similar way to ongoing work with Biogeochemical-Argo float data (Hyvernat et al., 2025).

Experiments run by the Met Office (MO) used a more complex 3D-Var assimilation scheme with multivariate balancing, and assimilated more variables. This showed greater impact from both physics and biogeochemistry assimilation, though with mixed impacts on the skill of variables and processes likely to be important for seasonal forecasting of biogeochemistry. Assimilating the full range of physics observations (SST, SSS, SLA, SIC, T&S) increased vertical velocities in the tropics and chaotic regions such as the Antarctic Circumpolar Current. This increased vertical mixing may be consistent with observational estimates at the very equator (Karnauskas, 2025), but is likely too large away from the equator and at depth (Karnauskas, 2025), with likely implications for seasonal prediction skill. It remains to be seen whether this is correcting or compensating for an error. The impact of assimilating ocean colour data depended on the multivariate balancing scheme used. The more complex scheme of Hemmings et al. (2008), designed for a simpler biogeochemical model, resulted in more widespread changes to biogeochemical variables, but often at the expense of model skill compared with both assimilated and non-assimilated data. This demonstrates the potential for such a scheme to maximise the information gain from satellite data, but suggests it needs tuning and development for each specific model configuration.

Taken together, some consistent conclusions emerge. Both physics and biogeochemistry satellite products clearly have potential to improve reanalyses and therefore seasonal forecasts. However, this requires assimilation schemes which are designed to fully exploit the information available, through multivariate and subsurface updates. For instance, using ocean colour data to only update surface phytoplankton has limited impact on biogeochemistry, although this can be locally large in regions such as the tropics. Using a multivariate balancing scheme originally designed for another model had a much wider impact, but not always positive. Schemes therefore need to be tuned and designed for specific model configurations, whether such schemes utilise balance relationships, ensembles, machine learning, or some combination. Whether gap-filled (level 4) or non-gap-filled (level 2 or 3) satellite data are required will depend on the assimilation method, and it would be useful for both to be available to the community. For assimilation though, daily products are likely to be more impactful than monthly ones. Furthermore, the combination of satellite and in situ data, for both physics and biogeochemistry, is expected to be fundamental for maximising skill.

Follow-on work, focussing on the MO system, will focus further on the role of physics assimilation on vertical mixing and biogeochemistry skill, and developing multivariate balancing schemes. Furthermore, coupled ocean-atmosphere-biogeochemistry reforecasts will be run, initialised from the different reanalyses presented here, to further examine likely prediction skill and optimal assimilation strategies.

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