Response to reviewers

Yumeng Chen

June 2026

We thank both reviewers for their detailed comments for improving the manuscript. Below is a response letter for the reviewers' comments. The green texts show our responses to the comments. The blue texts show our proposed changes in the revised manuscript. Due to the procedure of the journal, the revised manuscript is separated from the response letter. The final revised manuscript may have adjustments compared to the proposed changes here to improve the coherence of the revised manuscript.

Reviewer 1

Answer: We thank the reviewer for the useful comments on the manuscript. Before going to the point-by-point comments, we believe it would be beneficial to highlight the scope and aim of this study.

This study uses the widely used biogeochemistry model MEDUSA, which has been used for a variety of studies, including within the UKESM. The performance of MEDUSA is evaluated in the original model description paper and in various studies (e.g., Tagliabue et al., 2016; Sellar et al., 2019; Planchat et al., 2023). These provide a good quantification of the limitations and uncertainties of the model and as such further evaluation is not an objective for this manuscript.

We agree that the quality of different phytoplankton carbon products can differ, however, the purpose of this study is not to find the best phytoplankton carbon product. Instead, this study investigates the impact of assimilating a phytoplankton carbon product, i.e. asking the question what we can expect from assimilating these data in contrast to assimilating chlorophyll data, which is commonly assimilated. To our knowledge, whilst there are studies assimilating particulate organic carbon (POC), phytoplankton carbon assimilation is not well-studied in the literature.

Data assimilation can indeed assimilate various observations simultaneously. The relationship between different observations is specified by the observation error covariance matrix in DA. For most observations the observation errors are deemed uncorrelated. In our study, we do not assume correlated observation errors between phytoplankton carbon and chlorophyll, but we inflate the observation errors, which is a common approach. Assimilating multiple phytoplankton carbon products from ocean colour could complicate the study even more because we expect stronger observation error correlations between these products.

Major comments

1. Carbon products and phytoplankton product derived from remote sensing have been derived and used for years. There is no novelty in that and I am surprised you chose to only look at one such product. For example, Behrenfeld et al. (2005) showed how additional information can be gleaned from using a backscattering based C_phyto. In particular, through many manuscript, we have been able to show how phytoplankton photo-acclimation is the major forcing on the chl/C_phyto ratio and how it can inform us, for example, on nutrient limitation (`https://egusphere.copernicus.org/preprints/2025/egusphere-2025-4261/` ← it has been accepted). The point here is not to make you cite papers I contributed to but make you aware that the utility of estimate of C_phyto from space has been shown in many works and, in particular, in providing information content additional to Chl.

   Answer: The goal of this study is to investigate the effects of assimilating a phytoplankton carbon product on the ecosystem model. To our knowledge, the phytoplankton carbon derived from ocean colour has not been used in data assimilation for ecosystem modelling and forecasting but there are studies assimilating particulate organic carbon. We will include the utility of carbon products in our revised manuscript.

   However, it is also worth noting that carbon products derived from the backscattering of particles such as Behrenfeld et al. (2005) are based on empirical algorithms. The carbon product used in this study is underpinned by a different algorithm using a photoacclimation model (Sathyendranath et al., 2020). The chlorophyll-to-carbon ratio in the model varies as a function of the average, daily, photosynthetically active radiation available in the mixed layer. The carbon product is based on the derived chlorophyll-to-carbon ratio. Moreover, Sathyendranath et al. (2020) validated the chlorophyll-to-carbon ratio in their study whereas some carbon products, e.g., Aqua MODIS Level-4 Global Mapped Phytoplankton Carbon Data, has not yet been validated yet.

   We will rephrase the introduction to include relevant studies from L47:

   Besides chlorophyll data, other phytoplankton products, such as particulate inorganic ocean carbon and particulate organic ocean carbon, can be derived from satellite ocean colour (Siegel et al., 2005; Yang et al., 2024) independent of chlorophyll in their derivation. In particular, satellite ocean colour can be used to derive phytoplankton carbon (Behrenfeld et al., 2005; Graff et al., 2015; Bellacicco et al., 2020). These products are used to understand the ocean's biological pump and carbon cycles in addition to the phytoplankton carbon products (Siegel et al., 2023; Bourdin et al., 2025). Recently, in the ESA Biological Pump and Carbon Export Processes (BICEP) project, a new phytoplankton carbon (referred to as carbon hereafter) product has been derived from the ocean colour observations (Sathyendranath et al., 2021). The product is derived using an approach different from the backscattering of particles used in other carbon products. The new product is based on the chlorophyll-to-carbon ratio from a photoacclimation model where the ratio varies with the photosynthetically active radiation available in the mixed layer. Compared to other carbon products without sufficient assessments (e.g., NASA Ocean Biology Processing Group, 2025), the product's chlorophyll-to-carbon ratio is validated with field data (Sathyendranath et al., 2020). As this study focuses on the modelling response we opted to use an off-the-shelf observational dataset as opposed to developing our own derived product.

In this study, we explore the effects of assimilating the newly derived carbon product so that we can understand whether assimilating phytoplankton carbon can provide additional information compared with assimilating chlorophyll product alone. Note that, here, we do not seek the best carbon product for DA, but assess the general impact of such data in the DA process.

2. The first test of a good C_phyto product is whether its ratio to Chl is consistent with lab studies of photoacclimation, e.g. is $30 < \mathrm{C\_phyto/Chl} < 300$ (unless you are dealing with domination by mixotrophy in which case it could go lower, but you don't resolve them in your model.

   Answer: We agree that such an initial test is relevant when assessing the quality of a c_phyto product. However, this work focuses on investigating the effect of the assimilation of observations on the modelling system instead of the validation of the observation data itself, which is carried out by the data producers. Thus, we consider the observational data and the model as given and focus on the effects of the DA. The data are based on Sathyendranath et al. (2020), where the carbon product is derived based on the carbon-to-chlorophyll ratio. In Sathyendranath et al. (2020), the carbon to chlorophyll ratio is within the suggested range. The ratio is also broadly consistent with other studies as shown in their Figs. 7 and 8. We will include such information in the revision of the manuscript.

3. Field measurements of Fchl, as done with Argo floats, can have many biases (see Roesler et al., 2017). One has to be careful on how to use them.

   Answer: We will add this in L31 in the introduction. We will also point out the need for bias correction and better uncertainty quantification for data assimilation in the form:

   However, due to their recent deployment and the cost of instruments and their limited spatial coverage, satellite ocean colour is still a vital resource, especially on a global scale. For example, synthetic experiments performed by Ford (2021) did not address potential biases in phytoplankton chlorophyll of BGC-Argo floats because the chlorophyll is estimated from measurements of fluorescence (Roesler et al., 2017), which suggests the need for further research on bias correction in DA systems.

4. Phytoplankton products under clouds are typically wrong as they interpolate Chl rather than carbon and phytoplankton photo-adapt under cloud (`https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2024GL112274`). How they do it for the product you use could bias your model (70% of the ocean is covered by clouds at any given time).

   Answer: Based on the chlorophyll data product user guide of ESA OC-CCI (Jackson, 2020), the product does not contain data under clouds. This leads to spatial gaps in the product. Daily products only contain pixels with available observations. The composite monthly product is computed by averaging the available daily data over each month excluding missing data. The biases and uncertainties of the chlorophyll data product are validated by in situ observations. In data assimilation, we use bias-corrected chlorophyll data as observations and the uncertainties as the observation error. The carbon product is derived based on chlorophyll data and therefore inherits the treatment for data under clouds.

   In data assimilation, these sparse and irregularly spaced observations without interpolation can be assimilated. To obtain an analysis at a grid point, the data assimilation algorithm used in this paper assimilates observations adjacent to it within a radius. The update of the model grid point depends on the spatial correlation between the grid point and the observation locations derived from the ensemble forecast. This approach is well established and widely used in numerical weather prediction.

   We plan to add the information after L127:

   Both observation products do not contain information under clouds. Daily products only contain pixels with available observations. The composite monthly product is computed by monthly average of available daily data excluding missing data.

   In L108, we will add:

   The LESTKF can assimilate sparse and irregularly spaced observations without spatial interpolation of the observation product. In our configuration of the LESTKF, model variables on each grid point assimilate observations adjacent to it within a radius of 200 km. The DA increment on the grid points without observations is computed depending on the spatial correlation between the grid point and the observation locations.

5. How do you define the 'effectiveness' of DA is key and need to be provided. Obviously DA will force the model to the data.

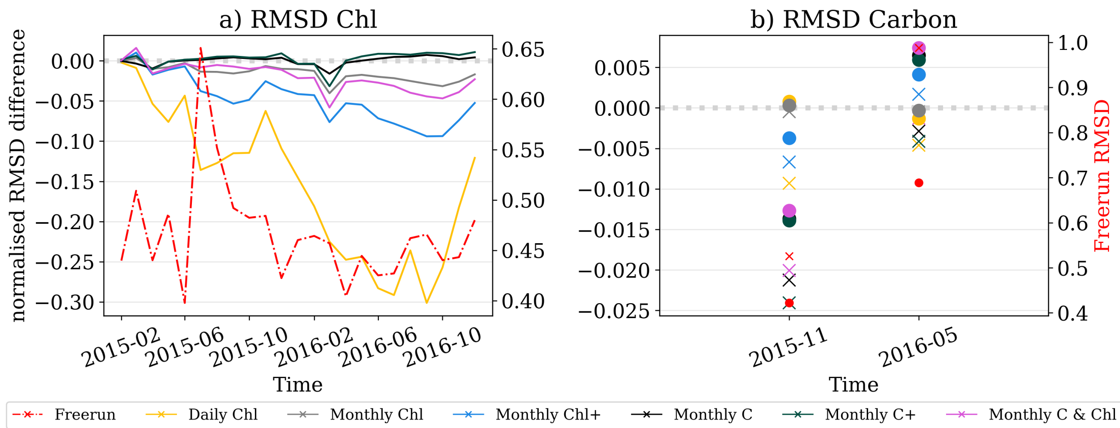

Figure 1: Differences of the RMSD between DA experiments and Freerun normalised by the RMSD of Freerun between the logarithm of monthly model forecast of and composite of the chlorophyll from Argo and field campaign data from NAAMES in left axis. The RMSD of Freerun is shown in dashed red line by right axis. The cross points represent comparisons with modelled total carbon while the dot points represent comparisons with modelled non-diatom carbon.

Answer: Indeed, by its very definition, DA will force the model to the assimilated data. The initially submitted manuscript focuses on the state adjustments induced by assimilating observations. In the revised manuscript, we will add an assessment of the state from data assimilation using BGC-Argo data for phytoplankton chlorophyll and in situ measurements from the North Atlantic Aerosols and Marine Ecosystems Study (NAAMES) for phytoplankton carbon assessment.

In Sect. 2.2, we will add a new subsection describing the independent observations.

Independent observations

To assess the DA system, we use in situ observations of chlorophyll and carbon data.

The in situ chlorophyll data are obtained from the BGC-Argo program (Group, 2016; Roemmich et al., 2019). The BGC-Argo program extends the Argo program, which is an international program that deploys automatic instruments floating with ocean currents. The BGC-Argo floats provide vertical profiles for both physical variables such as temperature, salinity, and pressure, and biogeochemical variables. In this study, only quality-controlled measurements with delayed-mode corrections from the upper 50 m were used, focusing the evaluation on the near-surface productive layer and the depth range most directly influenced by the DA. During the experiment period, the dataset has, on average, 448 observations per month.

The in situ observations of carbon is less common compared to chlorophyll. Here, we use the analytical measurements of phytoplankton carbon from North Atlantic Aerosols and Marine Ecosystems Study (NAAMES). The projects provide ship-based measurements for plankton stocks, rate processes, and community compositions. These in situ carbon observations are analytically determined for cells less than 64 μm using a BD Influx Flow Cytometer using methods detailed by Graff et al. (2015). Due to the limitation of the field campaign, the in situ datasets is limited to Northwest Atlantic and weeks of data in November 2015 and May 2016.

In Sect. 5.1.2, we will add:

We first compare our results with independent in situ observations in Fig. 1 with the root mean squared distance of the logarithm of chlorophyll and carbon between model forecast and the observations. The evaluation is performed on observation locations by linear interpolation from model grid points. For convenience, the point observations are considered as monthly averaged values, which could cause additional errors in this evaluation. The DA experiments show improvements compared to Freerun experiment as indicated by the negative values. All experiments assimilating chlorophyll show reduced RMSD compared to Freerun for chlorophyll. Experiments assimilating carbon show slightly increased RMSD of the chlorophyll. Because the carbon observations include only cells below 64 μm, we compare the observations with non-diatom phytoplankton in MEDUSA, which is considered small phytoplankton. assimilating chlorophyll has little impact on the RMSD of non-diatom carbon. The RMSD of non-diatom carbon (dot sign in Fig 1b)) is reduced by assimilating carbon in November 2015 but the RMSD is increased in May 2016. The increased RMSD by assimilating carbon in the RMSD of non-diatom carbon could be a result of post-processing and mismatch between the phytoplankton functional types, especially considering the seasonal dependence of the results. When comparing with total modelled carbon (cross sign in Fig 1b)), assimilating carbon better constrains the carbon than assimilating chlorophyll. For both carbon and chlorophyll, Daily Chl shows better performance than monthly assimilations. For monthly assimilation, simultaneous assimilation of chlorophyll and carbon provides a balanced RMSD compared to assimilating a single type of phytoplankton composition.

The assessment against in situ data is limited by the spatial and temporal coverage. Hence, we further evaluate the results by assimilated satellite data.

6. How are you converting C to N? The product is carbon and your model currency is N.

   Answer: We use a fixed Redfield ratio of C:N of 6.625:1. This follows the assumption used in the model formulation (Yool et al., 2013). We mentioned it in L96-L98:

   For consistency with the observed dataset the nitrogen fields in this study are represented as carbon, with the conversion between carbon and nitrogen following the model assumption of a fixed ratio between C:N of 6.625:1. For clarity, we describe nitrogen in terms of its carbon equivalent (hereafter referred to simply as "carbon")

7. To evaluate the distribution of parameter (e.g. histogram of distributions, whether of [Chl] or [Cphyto]), you could compare your model distribution to those of estimate from satellite. The near log-normal distribution should arise in both.

   Answer: The log-normal distributions of model and observation products are shown below. This study follows a common practice in biogeochemistry data assimilation, as shown in L140, where the state vector is transformed under a log-normal assumption, e.g., Ford and Barciela (2017); Pradhan et al. (2019). Although this is a basis for our choice of state vector and observations in the data assimilation system, we will not explore this in detail since using the log-transformation is common practice in the assimilation of chlorophyll data.

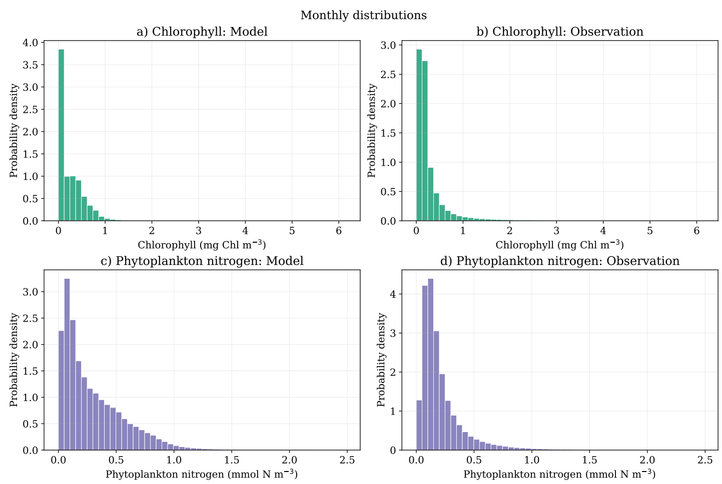

Figure 2: Distribution of phytoplankton in model and observation.

attached comments:

1. L30: Note that they measure fluorescence and not chlorophyll directly. There are many issues with these estimates (e.g., Roesler et al., 2017).

   Answer: See point 3 in major comments.

2. L34: Phytoplankton adjust their intercellular chlorophyll based on light and nutrients as well as species composition.

   Answer: We rephrase the corresponding sentence to:

   Assimilating satellite phytoplankton chlorophyll products, referred to hereafter as chlorophyll, can effectively reduce errors in modelled chlorophyll. However, even though the chlorophyll provides a proxy for biomass, assimilating chlorophyll does not necessarily correct other constituents of phytoplankton such as silicate, nitrogen and carbon as well as factors that constrain chlorophyll such as the availability of light, nutrients, and species composition.

3. L46: nor have they been validated.

   Answer: The data producers may disagree with this statement. For example, the PFT data from Losa et al. (2017) is validated against in situ data.

4. L47: What other relevant products? Are they independent from chlorophyll?

   Answer: We added that the particulate organic and inorganic carbon can be obtained independent of chlorophyll in their derivation. See point 1 in Major comments.

5. L50: There have been estimates of C_phyto from space produced at least from 2005 (see Behrenfeld et al., 2005). Again, the question is whether it is validated (the one of Behrenfeld was in Grag et al., 2015) and whether it provide additional information to [chl].

   Answer: We described the relevant observation products in the introduction. As mentioned, a major goal of this study is to investigate the potential benefits of assimilating phytoplankton carbon for global ecosystem modelling. Thus, we consider the question of whether there is potential additional information through the use of data assimilation which utilises multivariate relations from the model dynamics.

   See also point 1 in Major comments.

   In L52, we modify the text into

   In this study, we explore the effects of assimilating the carbon product so that we can understand whether assimilating phytoplankton carbon can provide additional information compared to assimilating chlorophyll product alone. Note that, here, we do not seek the best carbon product for DA.

6. L54: The first thing to do is to see whether you get realistic C_phyto/Chl ratios (should vary between 30 to 300 based on lab studies)

   Answer: See point 2 in Major comments.

7. L85: This is unfortunate as it has been shown that you do not get the correct heating rate in the spring w/o phytoplankton.

   Answer: We agree that marine biogeochemistry processes can have significant impact on physics (Manizza et al., 2005; Skákala et al., 2022). However, for operational systems that perform data assimilation, it is still uncommon to use two-way coupled models (Gehlen et al., 2015; Yumruktepe et al., 2022; Polton et al., 2023). Investigating the effects of two-way coupling is out of the scope of the paper. We will adjust the introduction here.

   The coupling to NEMO is one-way; that is, the marine ecosystem model is forced by the physical ocean, but has no feedback from the ecosystem to the physics. Although marine biogeochemistry processes can have significant impact on physics (Manizza et al., 2005; Skákala et al., 2022), the models in current data assimilation systems are still primarily one-way coupled (Gehlen et al., 2015; Yumruktepe et al., 2022; Polton et al., 2023). Hence, we acknowledge that the one-way coupling can limit the accuracy of the model forecast. Following the common practice of using one-way coupled model also allows us to avoid investigating the impact of two-way coupling, which is outside the scope of this work.

8. L89: No it is not. Currently phytoplankton role in CO_2 sequestration is similar to before the industrial revolution. It is the physical-chemical pump that is taking the excess anthropogenic CO2.

   Answer: Regardless of the impact of anthropogenic CO_2, a model incapable of simulating CO_2 uptake in marine ecosystems misses important climate processes. The missing processes are expected to impact climate models, which, depending on their complexities, attempt to capture the most prominent processes in the earth system. We change the text to remove mentioning climate prediction here.

   Beyond these components, MEDUSA is capable of simulating the CO_2 uptake of marine ecosystems. The carbon cycle simulation is enabled by the $p$$CO_2$, pH, alkalinity, and by carbonate species like H_2CO_3, HCO_3^- and CO_3^{2-}.

9. L94: I don't know if you are aware, but there are is significant portion of diatoms that are $< 20\mu m$.

   Answer: We agree that many diatoms are less than 20 μm so they are not strictly large phytoplankton by definition. In MEDUSA, a silicon biomass variable exists for diatoms but not for non-diatom phytoplankton. The diatom phytoplankton variable is responsible for silicon uptake and biogenic silica production and the non-diatom phytoplankton variable represents the non-silicifying phytoplankton community. However, the model also makes a simplified and idealised assumption that approximates the diatom phytoplankton functional type, which forms a key component of large phytoplankton, as "large phytoplankton". This is partly motivated by the interaction between phytoplankton and zooplankton, where small phytoplankton are strongly controlled by fast-growing microzooplankton whereas large phytoplankton are weakly controlled by slower-growing mesozooplankton.

   The manuscript will be modified:

   Phytoplankton biomass in MEDUSA is divided into diatom and non-diatom PFTs. The diatom phytoplankton variable is responsible for silicon uptake and biogenic silica production and the non-diatom phytoplankton variable represents non-silicifying phytoplankton community. To simplify the interactions between phytoplankton and zooplankton, MEDUSA models diatom phytoplankton as "large phytoplankton" based on the fact that diatoms are a key component of large phytoplankton even though diatom phytoplankton span a large range of sizes (Yool et al., 2011).

10. L114: You should check for that and for a reasonable carbon/chl ratio.

    Answer: See point 2 in Major comments.

11. L127: How it interpolates under clouds is important as clouds affect chl/c of phytoplanton (Begouen Demaux et al., 2025) and at any given time cover 70% of the ocean on average. Most product simply average chlorophyll over a month to fill the blanks due to clouds with clouds counting as NaN.

    Answer: See point 4 in major comments.

12. L139: See an earlier paper by Campbell

    Answer: Campbell (1995) will be added as reference.

13. L155: Is this an absolute value, a relative value or a mix of both?

    Answer: The errors of chlorophyll concentrations, ε, in the ESA OC-CCI data products are given for the logarithm of phytoplankton chlorophyll concentration. As such, it is an absolute additive error for the logarithmic concentration, which relates to a relative multiplicative error for the actual concentration.

    We will rephrase the text:

    For chlorophyll observations, σ_i is the same as the error provided by the observation product, which can be expressed as:

    $$\mathbf{y}_o^{\mu} = \mathbf{y}_t^{\mu} + \sigma, \tag{1}$$

    where $\mathbf{y}_t^{\mu}$ is the true logarithm of chlorophyll concentration and $\mathbf{y}_o^{\mu}$ is the observed logarithm of chlorophyll concentration. However, the carbon product does not provide an error estimate. In this study, the carbon observation error is estimated as the chlorophyll observation error inflated by 10%. This means that we assume the carbon error to be 1.1σ. ... Third, phytoplankton biomass is assumed to follow a log-normal distribution. Due to this assumption, observation errors expressed as the corresponding standard deviation of a Gaussian distribution are multiplicative instead of additive to observations:

    $$\mathbf{y}_o = 10^{\mathbf{y}_o^{\mu}} = 10^{\mathbf{y}_t^{\mu}} 10^{\sigma} = \mathbf{y}_t 10^{\sigma} \tag{2}$$

    This means that the errors are a scaling factor of the observation, regardless of the magnitude and unit of the observation itself.

14. L156: At low values the uncertainties can be O(100%) or more for both chlorophyll and C_phyto.

    Answer: Here, the phytoplankton chlorophyll error is inflated by 10% instead of giving an error of 10% of phytoplankton carbon value. Thus, the error of carbon is $10^{1.1\sigma}$.

15. L171: what to you mean by this? The two are correlated in nature too, though one is not derived from the other. The fact that chlorophyll changes from 0.01 to $50\mu g/l$ in the surface ocean and that the ratio of 30 < carbon/chl < 300 alone will cause them to be correlated.

    Answer: Data assimilation uses error covariance matrices of the forecast and the observations. What is relevant here is whether the errors are correlated, not whether the variables are correlated. For two independent measurements the errors of the measurements are not expected to be correlated even for the same physical quantity, which has a physical correlation of one. Here, because the carbon product is derived from chlorophyll, the observation error of chlorophyll is expected to propagate to the carbon product leading to error correlations.

    We will rephrase the text:

    Lastly, the error correlation between the phytoplankton products that arises because they are from the same satellite ocean colour measurements is neglected. If the carbon and chlorophyll products are measured independently, there are no error correlations between them. The neglected error correlations are assumed to be accounted for by the 10% inflation in the carbon observation errors. Recognising these potential issues, these results still provide an assessment of the value of the carbon product

16. L197: There are other product (e.g. backscattering) from which C_phyto can be derived at the same resolution as [chl]. While limit yourself to the databases you did?

    Answer: The limitation results directly from the motivation of our study: To investigate the effects of assimilating a carbon product on the modelling instead of finding the best carbon products for the DA system. Since the carbon product is recently derived via a different approach from the backscattering, and is easily accessible, we chose the current carbon product.

    See also point 1 in Major comments.

    We will adjust L52 to reflect this aspect.

    As this study is into the modelling response we opted to use an off-the-shelf observational dataset as opposed to developing our own derived product.

17. L213: How do you define ‘effectiveness’?

    Answer: Here, the ‘effectiveness’ is evaluated against the assimilated observations using biases between model and observations, the root mean squared differences (RMSDs), continuous rank probability score (CRPS), and ensemble spread. These scores are commonly used to assess DA.

We will adjust the text:

The global statistical metrics can provide the effect of DA. Here, the effectiveness of the DA is evaluated using the bias between model and observations, the root mean squared differences (RMSDs), continuous rank probability score (CRPS), and ensemble spread. These scores can expose potential disagreements between different observations, the uncertainty, and reliability of the ensemble after DA.

18. L219: What do you mean by this. Traceable? Validated?

    Answer: Here, it actually means un-biased observations or anchor observations. This concept comes from data assimilation for numerical weather prediction where some observations can have negligible biases so that one can perform bias correction in DA (Eyre, 2016).

    We rephrase the sentence to:

    Quantifying biases in models and observations is non-trivial considering the limited availability of so-called anchor observations with negligible biases (Eyre, 2016; Fowler et al., 2023)

19. L220: Aren't model parameters (e.g. grazing rates etc) tuned based on data, hence are not independent?

    Answer: We agree that the default model parameters are determined based on observations. However, ensemble Kalman filters in general assume no error correlations in time between observations, and uncorrelated forecast and observation errors. In the sequential DA the forecast is initialised by analyses subjected to observations at the time. If observation errors have time correlations, this could indeed lead to error correlations in observations and model forecast. Even though the assumption that observations have no time correlations is made partly based on computational considerations, it is a justifiable approximation.

    Considering that the model and its parameters were proposed earlier than the experiment period, its parameters have been tuned based on observations prior to the observations assimilated in this study. Hence, this allows to assume no correlations between model forecast and observation errors. Moreover, the misfit between observations and model forecast is widely used in the evaluation of operational DA systems, e.g., Saha et al. (2014); Zuo et al. (2019); Barton et al. (2021); Mignac et al. (2025)

    The manuscript will be adjusted as follows:

    Because DA methods assume uncorrelated forecast and observation errors, as a proxy, the bias can be revealed by the misfit between observations and the model forecast over multiple time steps used in the DA (Saha et al., 2014; Zuo et al., 2019; Barton et al., 2021; Mignac et al., 2025). The expectation of the misfit is zero without biases. Because the model parameters are not determined by the assimilated observations, this diagnostic can expose biases in the DA systems.

20. L230: Isn't this built in? Since your carbon is based on [chl] and since [chl] is biased low in the model, updating the [c] is akin of updating [chl] in the 'right' direction.

    Answer: Yes. This is a result of the model formulation where the nitrogen is the primary currency. This potential limitation is mentioned in the conclusion in L501: "Nevertheless, these adjustments may vary depending on the formulations of individual marine ecosystem models. In MEDUSA, carbon and nitrogen are assumed to have a fixed stoichiometric relationship. "

    We will adjust the manuscript with:

    Notably, using the balancing scheme to update the phytoplankton carbon in the "Monthly Chl+" experiment slightly improves the expectation of the misfits in chlorophyll. This suggests that making direct changes in the primary currency of phytoplankton biomass in MEDUSA leads to more sustained changes in the model.

21. L241: This may be driven by the fact that loss processes are just as important as processes contributing to growth (in nature).

    Answer: We will add the following sentence in the manuscript:

    If the concentration of nutrients is sufficient, increased chlorophyll would relate to an increased phytoplankton production, which is inconsistent with an overall lower carbon concentration from observations. This may also be driven by inaccurate modelling of the loss of phytoplankton in the coupling of phytoplankton chlorophyll and carbon. ...

22. page 9: Here and elsewhere, your model currency is N. Are you assuming a Redfield ratio to convert C:N?

    Answer: Yes. See point 6 in major comments as well.

23. L268: It is hard to evaluate what you mean by 'best'. Both model and data have biases, as you said, and once you assimilate the data the model output will look more like the data. How can you dependently assess what the best strategy is, e.g. by comparing to another INDEPENDENT data source.

    Answer: We agree that it is difficult to evaluate the best assimilation strategy. The intention of the comparison of RMSD is to show that the DA methods account for uncertainties in both observations when combining them with the model forecast, which has a global effect compared to assimilating a single type of observation.

    For further assessment, we will add an evaluation with ARGO data for chlorophyll and with in situ carbon data. See also point 5 in Major comments.

24. L295: isn't this by construction?; L298: Define 'reliable' ensemble

    Answer: A perfectly reliable ensemble means that the probability distribution function (p.d.f) of the ensemble is identical to the p.d.f of the truth (Leutbecher and Palmer, 2008; Rodwell et al., 2016).

    Data assimilation is constructed to improve the accuracy of state estimation using observations. In an ideal setup, the DA could improve reliability specified with a perfect forecast, observation, and model error covariance matrices without biases. However, it does not necessarily improve the reliability of the ensemble. For example, DA systems routinely have to deal with under-dispersive ensembles due to limited ensemble sizes (Carrassi et al., 2018). Therefore, it is not clear if assimilating multiple observations can improve the overall reliability of the ensemble.

    We will change the text in L282:

    In a perfectly reliable ensemble, the reliability score is zero. By definition, such an ensemble will have an probability distribution function identical to the true probability distribution (Leutbecher and Palmer, 2008; Rodwell et al., 2016). In this study, this is the probability distribution of the observations. The CRPS evaluates this on a grid point by grid point basis. The DA does not guarantee improved reliability by construction. Hence, this metric helps us evaluate the accuracy of quantified uncertainty from each experiment.

25. L469: My limited understanding is that the equilibration time of CO_2 and O_2 are very different in the upper. Can this affect what you see?

    Answer: The explanation will be added:

    Unlike pCO_2, the ocean surface oxygen concentration shows a strong seasonal variation without obvious trend, which could be a result of the different equilibration timescales of O_2 from pCO_2.

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