# Global Ocean Carbon Estimates in a Model Forced by MERRA

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## Abstract

MERRA reanalysis products were used to force an established ocean biogeochemical model to estimate carbon inventories and fluxes in the global oceans. The results were compared to public archives of in situ carbon data. The model exhibited considerable skill for ocean carbon inventories, i.e., dissolved inorganic carbon (DIC), and partial pressure of ocean $CO_2$ ($pCO_2$). For DIC, the model produced a global mean difference of 0.1% (approximately 1.8 μM) and basin-scale distributions were significantly correlated with observations ($r=0.98$, $P<0.05$). The model produced a global mean difference in $pCO_2$ of 0.2% (about 0.6 μatm) with positive correlation across oceanographic basins ($r=0.71$, $P<0.05$). Although model estimates of carbon flux ($fCO_2$) were within 35% of data, there was not a statistically positive correlation across ocean basins ($r=0.51$, NS). More troubling was the representation on the North Pacific and Antarctic basins as net sources of carbon to the atmosphere instead of a net sink indicated in the data and suggested by other efforts. Inadequate carbon uptake by biological primary production was the main cause of the excess carbon estimated by the model in the North Pacific, coupled with excessive convective overturn and local upwelling bringing high DIC concentrations from the deep ocean to the surface. In the Antarctic, most of the discrepancy was attributed to issues resulting from data scaling (using point observations to construct large scale representations), and inconsistencies between data sets of DIC and those of $pCO_2$ and carbon flux. Although the model results were encouraging for DIC and $pCO_2$, the flux results suggested model deficiencies

and also that large scale representations of data must be used cautiously when comparing with models. The results also suggested that MERRA is a viable source of forcing information for global ocean biogeochemical models with respect to carbon estimates.

## Introduction

The oceans play a critical role in the global carbon cycle. More than 90% of the active non-geological carbon pool resides in the oceans (Kaufman, 1998). Estimates of global primary production suggest that the oceans contribute about half (Field et al., 1998). One quarter (LeQuéré et al., 2010) to nearly one half (Sabine et al., 2004) of the carbon emitted by anthropogenic sources is thought to be sequestered in the oceans. Understanding the role of the ocean in the global carbon cycle is a driving question in modern Earth science. It requires foremost a geographically-distributed, well-maintained observational capability. We are fortunate that such a capability exists or is in development, and that global data sets of ocean carbon inventories (Key et al., 2004), partial pressure of $CO_2$ (Takahashi et al., 2006; 2009) and atmospheric exchange (Takahashi et al., 2006; 2009) are publicly available.

Numerical models containing explicit descriptions of the exchanges of carbon among biological and chemical constituents, and interacting with the atmosphere, can also assist in furthering the understanding of global ocean carbon cycling. Furthermore, such models can potentially aid in the forecasting of changes in the ocean carbon cycle based on anthropogenic and natural influences. Global ocean carbon models require external information to drive the ocean circulation dynamics that determine the distributions and abundances of carbon as well as biological and chemical constituents that play a role in the ocean carbon cycle. An ocean model of carbon dynamics is only as good as the fields needed to force it. These forcing fields typically come from publicly available reanalysis products (e.g., LeQuéré et al., 2010; Gorgues et al., 2010; Doney et al., 2009).

The Modern-Era Retrospective analysis for Research and Applications (MERRA) project represents a next generation of reanalysis products. Utilizing data from NASA Earth observing satellites, MERRA is intended to improve upon the widely recognized set of existing reanalysis products, primarily by including a more realistic representation of the hydrological cycle (Rienecker et al., 2011, this issue). A comprehensive approach using advanced data assimilation

methodologies and modern Earth remote sensing observations, along with state of the art atmospheric and hydrological models, MERRA is expected to fully support climate-related modeling efforts.

Here we use MERRA reanalysis products to force a global ocean biogeochemical model. We seek to 1) simulate the distributions and fluxes of carbon components in the global oceans with an explicit, prognostic description of the carbon cycle and 2) evaluate the realism of the model results. The simulation is accomplished using an established three-dimensional model of the global oceans containing prognostic representations of biological and chemical constituents involved in the ocean carbon cycle. Evaluation is achieved through comparison with observations of carbon inventories and fluxes.

# Methods

### *Global Three-Dimensional Circulation Model*

Global ocean carbon dynamics are simulated by the NASA Ocean Biogeochemical Model (NOBM; Figure 1). It is a three-dimensional representation of coupled circulation/biogeochemical/ radiative processes in the global oceans (Gregg et al., 2003; Gregg and Casey, 2007). It spans the domain from $-84^{o}$ to $72^{o}$ latitude in increments of $1.25^{o}$ longitude by $2/3^{o}$ latitude, including only open ocean areas, where bottom depth>200m. The biogeochemical processes model contains 4 phytoplankton groups, 4 nutrient groups, a single herbivore group, and 3 detrital pools (Figure 2). The phytoplankton groups differ in maximum growth rates, sinking rates, nutrient requirements, and optical properties. The 4 nutrients are nitrate, regenerated ammonium, silica to regulate diatom growth, and iron. Three detrital pools provide for storage of organic material, sinking, and eventual remineralization back to usable nutrients.

Carbon cycling involves dissolved organic carbon (DOC) and dissolved inorganic carbon (DIC; Figure 2). DOC has sources from phytoplankton, herbivores, and carbon detritus, and a sink to DIC. DIC has sources from phytoplankton, herbivores, carbon detritus, and DOC, and communicates with the atmosphere, which can be either a source or sink. The ecosystem sink for DIC is phytoplankton, through photosynthesis. This represents the biological pump portion of the carbon dynamics. The solubility pump portion is represented by the interactions among temperature, alkalinity (parameterized as a function of salinity), silica, and phosphate

(parameterized as a function of nitrate). The alkalinity/salinity parameterization utilizes the spatial variability of salinity in the model adjusted to mean alkalinity

$$TA = \underline{TA}\ S/\underline{S}$$

where TA is total alkalinity and S is salinity. The underscore represents global mean values. $\underline{TA}$ is specified as 2310 μE $kg^{-1}$. The phosphate/nitrate parameterization involves multiplying the model nitrate by 0.1, which is derived from the global mean ratio from the National Oceanographic Data Center (Conkright et al., 2002) for the top three standard levels. The calculations for the solubility pump follow the standards set by the Ocean Model Intercomparison Project (OCMIP; www.ipsl.jussieu.fr/OCMIP). We employ a lookup table specified over modern ranges of DIC, salinity, temperature, and nutrients for computational efficiency, at no cost to accuracy.

NOBM undergoes spin-up for 35 years under climatological forcing. Initial conditions for DIC are derived from the Global Data Analysis Project (GLODAP; Key et al., 2004). We average DIC over oceanographic basins and depth and use these mean values for initial conditions. A maximum deep value of 2330 μM is enforced (Goyet et al., 2000). DOC initial conditions are set to 0 μM. Other initial conditions are described in Gregg and Casey (2007).

***Data Sets***

*Forcing Data Sets*

Forcing data sets are shown in Figure 1. Monthly climatologies are used in all cases. All except soil dust (iron), ozone, clouds, and atmospheric $CO_2$ are obtained from MERRA products. Ozone is from the Total Ozone Mapping Spectrometer, and soil dust deposition is from Ginoux et al. (2001). Cloud data (cover and liquid water path) are obtained from the International Satellite Cloud Climatology Project. Atmospheric $CO_2$ is taken from the Lamont-Doherty Earth Observatory (LDEO) data set (Takahashi et al., 2009), using a mean over the entire range of observations of 358.7 μatm.

*Comparison Data Sets*

The main outputs of interest in this effort are dissolved inorganic carbon (DIC), representing the inventory of total $CO_2$ stored in the oceans, partial pressure of $CO_2$ ($pCO_2$), and the flux of $CO_2$ ($fCO_2$), representing the exchange of carbon between the atmosphere and ocean (positive is defined upward, indicating a source to the atmosphere). DIC data sets are obtained from

GLODAP (Key et al., 2004), which are mapped on a 1° horizontal grid with 33 standard depth levels (http://cdiac.ornl.gov/oceans/glodap/). $pCO_2$ and $fCO_2$ data sets are mapped on a 5° longitude by 4° latitude horizontal grid and are surface only. They are obtained from LDEO (http://cdiac.ornl.gov/oceans/LDEO_Underway_Database/index.html; Takahashi et al., 2009).

We also derived an alternative representation of $pCO_2$ and $fCO_2$ from GLODAP DIC using the OCMIP protocols. This enables us to understand the consistency between the publicly available ocean carbon data archives. Here we require several data sets, including wind speed, SST, and sea level pressure, which are obtained from MERRA, nitrate (a proxy for phosphate like in the model), salinity and silica, which are obtained from NODC. Atmospheric $pCO_2$ is used as for the model, a constant value representing the mean of the LDEO observations.

***Methodological Approach***

The global model NOBM is forced with the MERRA variables shown in bold in Figure 1. The model is spun up for 34 years using monthly climatologies of MERRA forcing. In the 35th year of simulation, model results of surface DIC, $pCO_2$, and $fCO_2$ are compared graphically and statistically with climatological in situ data sets from GLODAP and LDEO. Results are evaluated globally and regionally in 12 major oceanographic basins (Figure 3). Statistical comparisons include global and basin differences between model and data global and regional means, expressed as percent, and correlation analysis. Our emphasis is on large scale results, so our correlation analysis is performed across the basins (so that N=12, with 10 degrees of freedom). All analyses here are performed for annual mean results, and the data sets are converted to the NOBM spatial grid prior to comparison.

We are also interested how fording fields affect the estimate of global carbon. We run NOBM using reanalysis products from the NOAA/National Center for Environmental Prediction (NCEP; Kalnay et al., 1996). We also use data from LDEO in a third forcing test of the model. This is only partial in terms of forcing fields, as only sea surface temperature, sea level pressure, and wind speed are available in the data set. The remaining variables required from Figure 1 are from MERRA.

# Results

***Comparison of NOBM Carbon with Data Sets***

Surface DIC from NOBM compares favorably with in situ data (Figure 4). There is substantial geographical similarity, and basins follow similar patterns. The global difference is 0.1%, with a correlation across basins of 0.98, which is statistically significant at $P<0.05$. The most notable differences are the tropical upwelling regions. Upwelling in the Equatorial Pacific is not apparent in the in situ data, while it is prominent in the model. The in situ data show a depression in DIC in the Equatorial Atlantic upwelling region, which is in contrast to an increase seen in the model. The basin mean, however, is in agreement. There is less disagreement in the North and Equatorial Indian basins, but there is lower DIC in the western portions in the model, and somewhat more in the eastern portion.

There is also considerable similarity between the model and in situ data in global $pCO_2$ distributions (Figure 5). The global difference is 0.2% and the correlation across basins is statistically significant with $r = 0.71$. The model $pCO_2$ distributions are in agreement in the tropical Pacific upwelling, in contrast with DIC, and there is no depression in the tropical Atlantic in the data. The model shows an enhancement of $pCO_2$ in the Equatorial Atlantic upwelling, similar to the DIC. There is an east-west departure in the North and Equatorial Indian basins between the model and data, as with DIC, with lower values in the model in the west, and higher values in the east. The largest discrepancy is the South Atlantic, where the model $pCO_2$ is 28 µatm lower than the data, which represents a 7.8% difference. There is also a region of depressed $pCO_2$ in the northeastern South Pacific, which does not appear in the data. The Antarctic $pCO_2$ in the model is higher than the data by about 7.8 µatm, which is about 2.2%.

There are many areas of agreement in the flux of $CO_2$ ($fCO_2$) between the model and data, but there are also many areas of disagreement and they are more pronounced than with DIC and $pCO_2$ (Figure 6). The global difference is nearly 35%, representing 0.12 mol C $m^{-2}$ $y^{-1}$. Furthermore, the basin correlation is not statistically significant. There are two basins where the sign of the flux is different: the Antarctic and the North Pacific (Figure 6). A large difference between the model and data occurs in the South Atlantic. However, the sign of the flux here is the same.

A scatterplot (Figure 7) reinforces the difference in model and data carbon flux by basin. The two basins where the sign of the flux is reversed are clearly apparent in the first quadrant, but all the other basins are in the proper quadrant. The tropical basins are clustered in the second quadrant, indicating positive flux (source) to the atmosphere. The remaining basins are all

negative flux, representing a sink of $CO_2$ from the atmosphere, although there are differences in the amounts.

***Comparison between Model Forced by MERRA and Forced by NCEP and LDEO***

Basin and global means of $fCO_2$ from the model forced by MERRA are compared to the same model forced by NCEP and LDEO (Figure 8), illustrating generally close agreement. The largest departures are in the North and South Indian basins. These results reinforce the basin annual means shown earlier (Figure 6). These patterns are preserved regardless of the choice of forcing between MERRA, NCEP, or LDEO. Stronger agreement is achieved for DIC, where the differences in forcing produces basin changes <3 μM, and for $pCO_2$, for which the maximum basin change is <4 μatm and the global difference is within 1 μatm, regardless of the forcing source (data not shown).

***Comparison between Carbon Data Sets***

Using surface DIC data from GLODAP (Key et al., 2004) along with climatologies of surface variables we are able to construct an estimate of $fCO_2$ consistent with the GLODAP data set. Global and basin distributions and means of $fCO_2$ from GLODAP DIC indicate major departures from the in situ data sets of Takahashi et al. (2009) (Figure 9). GLODAP-derived $fCO_2$ is considerably lower than the data in the North Atlantic, and much higher in the Antarctic. The North Pacific, Antarctic, and South Atlantic basins exhibit stronger correspondence with the model than with the data. The North Atlantic $fCO_2$ is a very strong sink as represented by GLODAP, so much that it is off-scale in Figure 9. The South Indian also shows a strong sink, although less so, and is in disagreement with the model estimates and data.

## Discussion

The MERRA-forced model (NOBM) produces remarkable agreement with in situ data sets for DIC and $pCO_2$. The global mean difference is 0.1% and 0.2%, respectively, and both show statistically positive correlation with data ($P<0.05$) across the 12 major oceanographic basins. We acknowledge that that agreement for DIC is perhaps not surprising, since it was used for initial conditions. But the ability of the model to hold these large scale distributions, and also exhibit substantial agreement with smaller scale distributions (Figure 4), suggests that NOBM, forced by MERRA atmospheric and oceanic variables, possesses considerable skill for simulating ocean carbon inventories.

The agreement of the MERRA-forced model with data for DIC and $pCO_2$ is not repeated as strongly for carbon fluxes ($fCO_2$). A larger global mismatch is observed (about 35%) and the basin correlation is not statistically significant at $P<0.05$ (Figure 6).

The model exhibits skill in the $fCO_2$ comparison, however, such as the tropical basins and North Atlantic (Figure 6). Also smaller scale regions in the South Indian and South Pacific where a large sink occurs are in agreement, as well as the sink area near $30^o$ in the northern Pacific. Globally the 35% difference does not produce a change in sign and can be considered relatively small.

However, there is considerable uncertainty in the flux estimates as represented by the standard deviation both globally and on basin scales. The model exhibits larger uncertainty, but the lower values in the data are likely a result of the smoothing to $5^o$ longitude by $4^o$ latitude in the data (Takahashi et al., 2009), along with considerable large scale gap-filling (Takahashi et al., 2009). It is most disconcerting that two basins, the Antarctic and the North Pacific, have an opposite flux (source to the atmosphere) in contrast to the data (sink to the ocean).

We note that, our basin correlation holds small N (12, with 10 degrees of freedom), making it difficult to obtain statistical confidence. We are most interested in the model skill at global and basin scales, however, and consider this approach appropriate. However, we note that at a one-to-one matchup at the model grid scale ($1.25^o$ longitude by $0.67^o$ latitude) we obtain statistically positive correspondence with data for $fCO_2$ with admittedly low correlation coefficient ($r=0.38$, $P<0.05$, $N=38885$, data not shown).

Since DIC is a strong contributor to $pCO_2$, and $pCO_2$ is a strong contributor to $fCO_2$, the results suggest that skill in reproducing ocean carbon constituents does not necessarily translate to skill in reproducing ocean carbon fluxes. Small discrepancies between model and data in DIC and $pCO_2$ can produce important differences in $fCO_2$. Thus $fCO_2$ is sensitive to small errors in DIC and $pCO_2$.

The largest basin discrepancies in carbon flux between model and data are the Antarctic and North Pacific, where NOBM suggests a source and the data indicate a sink (Figures 6 and 7). Most other work using models, inversions, and data support the data results shown here (Gruber et al., 2009). The South Atlantic represents a more minor discrepancy because the estimated flux has same sign as the data (Figure 6). However, it is much more extreme. There are of course several local differences but we focus here on the large scale problems.

We attempt to explain these large scale model-data discrepancies by emphasizing 4 main possible causes:

1) Data scaling
2) Differences in forcing fields
3) Inconsistencies between data sources, specifically LDEO and GLODAP
4) Model issues

***Data Scaling***

Public data sets of $pCO_2$ and $fCO_2$ (Takahashi et al., 2009) are taken from point measurements in the ocean, gridded to $5^o$ longitude by $4^o$ latitude, binned to an annual mean climatology, and with residual gaps filled. Additionally, years corresponding to El Niño events are excluded for the tropical Pacific (Takahashi et al., 2009). Each of these steps potentially introduces a bias in the final result, which we refer to here as data scaling issues. Binning to a coarse grid reduces variability and over-represents the influences of observation points closest to gaps. Constructing annual means where data exist for only a few months creates an unbalanced representation, with the sampled months over-represented. If the sampled months occur at a low or high point in the seasonal cycle, the problem is exacerbated. A typical example is sampling only in January in the Southern Ocean, when temperatures and primary production are highest. Filling gaps, like binning to a coarse grid, over-represents the influence of observations nearest the gaps unless methods are actively used to reduce this problem. Takahashi et al. (2009) used an interpolation scheme based on assumed advective transport. Finally, removing El Niño events in the tropical Pacific over-represents La Niña events in the climatology.

However, shipboard underway data at the location of data measurement, ungridded, with temporal sampling identified, with sampling gaps preserved, and inclusive of all years sampled, are also available (http://cdiac.ornl.gov/ftp/oceans/LDEO_Database/Version_2009/). Using these raw observations we can re-construct the representation of $pCO_2$ data at our model grid. By sub-sampling the model by the data locations, we can remove the mismatches due to data scaling, and produce an unbiased, one-to-one comparison. The resulting images show the sparseness of the sampling and suggest the potential for biases through the data scaling efforts (Figure 10).

Focusing on the basins with the worst data comparisons, we see that about 40% of the difference in $pCO_2$ in the Antarctic is due to data scaling (Figure 11). This suggests data scaling

is a large contributor to the model-data difference here, but does not completely explain it. The North Pacific exhibits less proportion of the difference due to scaling, about 21%, but again the scaling is a contributor to the difference. Nearly 70% of the discrepancy observed in the South Atlantic, another problem area in the comparison, is explained by data scaling. This suggests that the binning to $5^o$ by $4^o$ in the gridded data sets produces a representation of higher $pCO_2$ than is indicated by the raw data. Interestingly, the data scaling analysis suggests that model-data discrepancies are masked by the gridded representations in the Equatorial Indian and to a lesser extent the Equatorial Pacific. Overall the sub-sampled model-data comparison shows a statistically positive global correlation ($r=0.33$, $P<0.05$, bias=7.1, RMS=40.4, N=24449)

Carbon flux estimates are not available in the raw data from LDEO, but we can estimate them from $pCO_2$ and climatological ocean and atmospheric variables using the OCMIP protocols, similar to the way $fCO_2$ is computed by the model. The required variables are silica, nitrate (a proxy for phosphate), salinity, temperature, wind speed, sea level pressure, and atmospheric $pCO_2$. While all of these are derived from or force the model in the model derivation of $fCO_2$, we use data climatologies here to estimate $fCO_2$ from the LDEO $pCO_2$ point measurement data. In this case, nitrate and silica are taken from NODC, and the rest from LDEO to retain as much consistency as possible.

The $fCO_2$ results suggest that data scaling plays a major role in the estimated differences between the model and data (Figure 11). For the Antarctic, the difference between the model and data $fCO_2$ nearly disappears when scaling issues are removed. This does not mean that the data now suggest a source rather than a sink, as the model does, because the basin mean $fCO_2$ is still negative in the data. However, it is only slightly so (-0.005 mol $m^{-2}$ $y^{-1}$) and the sub-sampled model has declined from 0.42 to 0.13 mol $m^{-2}$ $y^{-1}$. However, the dramatic reduction in the difference suggests a strong influence of data scaling issues in the full model and data comparisons. The other major problem basin, the North Pacific, also exhibits major improvement when scaling differences are accounted for. Here the difference falls to less than half the full representation (Figure 11). Like the $pCO_2$ results, the scaling appears to contribute about 70% of the model-data difference seen in the South Atlantic in the full model-data comparisons. Strikingly, the previous discrepancy observed in the South Pacific has now virtually disappeared when scaling issues are removed. Overall the sub-sampled model-data

comparison shows a statistically positive global correlation (r=0.33, P<0.05, bias=0.098, RMS=1.04, N=25012)

***Forcing Data***

Forcing data are critical for the proper evolution of a forward biogeochemical model, and the use of MERRA data sets can potentially contribute to the representation of carbon inventories and fluxes observed here. Other ocean carbon modeling efforts have typically utilized NCEP forcing data (e.g., LeQuéré et al., 2010, Doney et al., 2009; McKinley et al., 2004), so we compare our MERRA forced results from a separate model integration utilizing NCEP forcing (Figure 8). The differences in resulting carbon fluxes, the most sensitive of the carbon representations, are small globally and in most basins. An exception is the North Indian, which shows a larger discrepancy for the NCEP-forced model than the MERRA forced. Differences between the forcing for DIC and $pCO_2$ are even smaller than $fCO_2$ (data not shown). We conclude that the model results are relatively insensitive to the differences in forcing by MERRA and NCEP or LDEO, at least regarding ocean carbon estimates, and do not explain the major discrepancies in the model-data comparison observed here. Similar results are obtained using LDEO forcing fields (Figure 8).

***Data Set Inconsistencies***

NOBM, like many global ocean biogeochemical models (e.g., LeQuéré et al., 2010, Doney et al., 2009) uses GLODAP DIC data for initialization. The initialization creates the inventory of DIC that is subsequently advected, diffused, taken up and given off by biological processes and exchanged with the atmosphere as a function of the $pCO_2$ which is ultimately derived from it. One of the successes of the MERRA-forced NOBM is the close correspondence between the resulting DIC fields and the GLODAP data (0.1% global difference, correlation coefficient across ocean basins or 0.98, P<0.05; Figure 4), which should be regarded with some skepticism considering the use of GLODAP in the initial conditions. But considering the complex processes affecting DIC inherent in the model, and that mean DIC over basins and depths are used for initial conditions, the results should also not be dismissed.

Here we ask how much the model discrepancies can be traced to the GLODAP DIC data set, and how much the DIC data set and the carbon $pCO_2$ and flux data from LDEO are consistent. GLODAP-derived estimates of $fCO_2$ show many areas of correspondence with LDEO data sets (Figure 9), such as subtropical South Indian and Pacific basins, the subarctic North Pacific, and

the North Atlantic in general. Upwelling areas in the Equatorial Pacific and Atlantic are not apparent in the GLODAP-derived $fCO_2$, as DIC was not apparent originally. It is interesting that the model actually reconciles the missing GLODAP DIC-$fCO_2$ equatorial upwelling, resembling more the LDEO distributions (Figures 6 and 9). The Antarctic exhibits a major discrepancy.

In general, basin mean GLODAP-derived $fCO_2$ agrees more with the model than with the LDEO data (Figure 9). The positive carbon flux in the Antarctic estimated in the model is nearly replicated by GLODAP. The high DIC represented by GLODAP and preserved by the model here is a major contributor to the discrepancy in carbon flux, and suggests and inconsistency between the GLODAP DIC and LDEO $pCO_2$ and $fCO_2$ data sets. A similar agreement between model and GLODAP-derived $fCO_2$ occurs in the South Atlantic and also similarly disagrees with LDEO suggesting inconsistency. This pattern is similar in the North Pacific but less so. While the basin mean GLODAP-derived $fCO_2$ is more similar to the model than the data in the North Pacific, we note that the areas of high $fCO_2$ are not similar. The model is highest in the Sea of Okhotsk and western Bering Sea while the GLODAP $fCO_2$ is highest in the central North Pacific, suggesting that high DIC is not a cause of the discrepancy between model and data carbon flux. We note extremely high negative fluxes occur in the North Atlantic near the mouth of the Labrador Sea affecting the entire basin representation in the GLODAP-derived $fCO_2$ that appears to be result of a convergence of anomalous climatological data and DIC.

Considering that the discrepancies in $fCO_2$ observed in the Antarctic and South Atlantic are replicated in the GLODAP-derived $fCO_2$, this suggests that the discrepancies are either partially derived from the GLODAP DIC initial conditions, or that similar data scaling issues reported earlier are also contributing to the GLODAP-LDEO $fCO_2$ differences. An alternate explanation is that there is a combination of these two influences. However, the suggestion that there are inconsistencies between carbon representations of DIC by GLODAP and $pCO_2$ and carbon fluxes by LDEO is a possibility.

***Model Issues***

NOBM is an imperfect representation of carbon dynamics in the global oceans. Although a considerable amount of the mismatches between the model and data can be attributed to data scaling and data set inconsistencies, errors in the model play an important role as well. The most important discrepancy with the largest implications is the North Pacific, where the model indicates a source, deriving from too high $pCO_2$. We believe this is erroneous and is caused by 2

model flaws: 1) insufficient primary production and 2) excessive convective mixing of deep DIC. Both of these errors occur especially in the northwest North Pacific and the Sea of Okhotsk (Figures 5-8). Although on a basin scale the GLODAP-derived $fCO_2$ also produced the erroneous carbon source, the location of the high $pCO_2$ and DIC are not in the same place as the model. The western North Pacific is an area of massive seasonal temperature variability resulting in deep convective mixing, and is also a region of local upwelling, both of which bring deep DIC initialized by the GLODAP data set to the surface, producing the high $pCO_2$ and ultimately high carbon flux to the atmosphere. Primary production appears to be suppressed in the model preventing uptake of this deep DIC. Together these processes produce the ingredients for excessive surface carbon, which in turn produce the expression of carbon flux to the atmosphere. Our evidence for the suggestion of inadequate primary production derives from the comparison of NOBM chlorophyll with estimates from remote sensing (Figure 12). We believe primary production is suppressed by the radiative transfer model used in NOBM, since nutrients in the North Pacific are plentiful (data not shown).

Two other regions where we suggest model error predominates are the North and Equatorial Indian basins. Here the data indicate a strong source to the atmosphere in the western portion, and a modest sink in the east. The model shows the opposite. In the model the strong sink in the western North and Equatorial Indian is due to very high primary production, depleting carbon from the surface layers through photosynthetic uptake. The east is suppressed because of lack of nitrate.

These two basins are not the only regions where model error occurs in the estimation of ocean carbon inventories and fluxes. There are many local discrepancies that must be explained by deficiencies in the model. However, these two examples provide the most glaring examples of model flaws and have the most important implications for the model representation of global carbon dynamics and estimates.

## Summary

A global ocean biogeochemical model is forced by MERRA reanalysis products to estimate the state of ocean carbon inventories and fluxes. The carbon estimates are quantitatively compared to in situ data sources. The results suggest the model demonstrates considerable skill for ocean

total carbon inventories, expressed as dissolved inorganic carbon (DIC), and partial pressure of ocean $CO_2$ ($pCO_2$). For DIC, the model produces a global mean difference of 0.1% (approximately 1.8 μM) and the basin-scale distributions are significantly correlated with observations ($r=0.98$, $P<0.05$). Similarly, the model indicates a global mean difference in $pCO_2$ of 0.2% (about 0.6 μatm) with positive correlation across oceanographic basins ($r=0.71$, $P<0.05$). These encouraging statistical results are unfortunately somewhat misleading when considering carbon exchange with the atmosphere, which is highly sensitive to small discrepancies in DIC and $pCO_2$. For carbon flux ($fCO_2$), we find less positive comparisons with in situ data: global mean difference of 35% (0.12 mol C $m^{-2}$ $y^{-1}$) and no statistically positive correlation across the oceanographic basins at a 95% confidence level ($r=0.51$, NS). These discrepancies are primarily the result of issues in three ocean basins: the Antarctic, North Pacific, and South Atlantic. The Antarctic and North Pacific are the most troubling because in the model they indicate a net source of carbon from the ocean to the atmosphere, while the data indicate a net sink. The South Atlantic shows a large difference between model and data estimates, but the sign of the carbon flux is at least the same (net sink).

Forcing by MERRA reanalysis products does not appear to contribute to the observed discrepancies between the model and data. When the model is forced by NCEP and LDEO products, the resulting carbon estimates are generally similar. Instead, the departures appear to be a combination of model errors, data scaling issues in the in situ data, and inconsistencies between major public global archives of carbon inventories and fluxes in the oceans.

Insufficient uptake of carbon via primary production is the main cause of excessive carbon estimated by the model in the North Pacific. This, coupled with high convective exchange of high carbon concentrations in deep water along the western portion of this basin and in the Sea of Okhotsk, along with local upwelling, produces high $pCO_2$ and a net positive $fCO_2$ to the atmosphere. The model also appears to be the culprit for east-west local discrepancies in the North and Equatorial Indian basins. However, in this case the model error is excessive primary production in the western portions of the basins, taking up more carbon than indicated by the data and producing a localized strong sink, in contrast with the observations.

Although the model formulation contributes to the discrepancies seen in other ocean basins, issues with data scaling and inconsistencies between data sets appear to play a more important role. By data scaling we refer to the process of taking discrete point measurements, binning

them to a coarse grid, combining them temporally to produce annual means despite uneven sampling, and filling gaps. Each of these steps potentially produces a bias in large scale data representations. Data scaling appears to be a major contributor to the discrepancies between model and data $fCO_2$ in the Antarctic. In addition there are data inconsistencies, namely that GLODAP observations of DIC and the resulting estimates of $pCO_2$ and $fCO_2$ do not agree with LDEO data sets of the same variables. Since the model agrees with the GLODAP estimates of DIC, this inconsistency, coupled with data scaling issues, appears to explain the difference between the model and data here. A similar convergence of issues in data scaling and data inconsistencies may be responsible for the model-data discrepancies in the South Atlantic.

We do not suggest that data scaling issues mean that the global scale representations of $pCO_2$ and $fCO_2$ data are incorrect. We simply point out that when comparing model results to data, it is important to compare as closely as possible to the actual data locations, and not where they have been expanded to represent large scale estimates.

A global ocean model forced by MERRA reanalysis products appears to be capable of producing reasonable estimates of global DIC and pCO2, but estimates of carbon flux have some issues. However, these issues do not appear to be related to the MERRA products and the overall large scale agreement in many carbon variables suggests that MERRA is a quality source of atmospheric and surface ocean forcing products to support models of global ocean carbon.

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