Relationship between Ocean Carbon and Heat Multidecadal Variability

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ABSTRACT

The global ocean serves as a critical sink for anthropogenic carbon and heat. While significant effort has been dedicated to quantifying the oceanic uptake of these quantities, less research has been conducted on the mechanisms underlying decadal-to-centennial variability in oceanic heat and carbon. Therefore, little is understood about how much such variability may have obscured or reinforced anthropogenic change. Here the relationship between oceanic heat and carbon content is examined in a suite of coupled climate model simulations that use different parameterization settings for mesoscale mixing. The differences in mesoscale mixing result in very different multidecadal variability, especially in the Weddell Sea where the characteristics of deep convection are drastically changed. Although the magnitude and frequency of variability in global heat and carbon content is different across the model simulations, there is a robust anticorrelation between global heat and carbon content in all simulations. Global carbon content variability is primarily driven by Southern Ocean carbon variability. This contrasts with global heat content variability. Global heat content is primarily driven by variability in the southern midlatitudes and tropics, which opposes the Southern Ocean variability.

1. Introduction

The global ocean is an important component of the climate system. Holding far more heat and carbon than the atmosphere, it is an important sink for anthropogenic carbon and heat generated from greenhouse gas emissions. Observational estimates suggest that as of 1995, the ocean has been responsible for the uptake of approximately 100 Pg of anthropogenic carbon (Khatiwala et al. 2012; Sabine et al. 2004; Waugh et al. 2006). Temperature observations have also been used to estimate that the upper 2000 m of the ocean has been a sink for 15×10^{22} J of excess heat (Levitus et al. 2009) between the years 1975 and 2005. Additionally, Frölicher et al. (2015) demonstrated that in climate model simulations the Southern Ocean is an important region for oceanic uptake of anthropogenic carbon and heat. They estimate that 30% of anthropogenic carbon and 75% of anthropogenic heat that enters the ocean does so south of 30°S.

However, changes in the circulation due to both anthropogenic forcing and natural variability may play an important role in heat and carbon uptake. Many studies have examined how changes in Southern Ocean circulation impact ocean carbon content (Sarmiento and Toggweiler 1984; Sarmiento and Le Quéré 1996; Marinov et al. 2008). Between the 1980s to early 2000s, multiple studies linked an acceleration of the wind-driven Southern Ocean overturning with the resulting increase in upwelling of carbon-rich waters, resulting in a decrease in the Southern Ocean CO₂ sink despite an increase in atmospheric CO₂ (Le Quéré et al. 2000; Lovenduski et al. 2007; Lenton et al. 2009). More recently, however, observational studies have suggested that this weakening of the Southern Ocean carbon sink has reversed (Landschutzer et al. 2015; Devries et al. 2017), highlighting the importance of understanding natural variability. Finally, in many models, Weddell Sea deep convection has been determined to cause large fluctuations in ocean heat (Latif et al. 2013; de Lavergne et al. 2014) and carbon content (Bernardello et al. 2014). While significant effort has gone into understanding the net uptake of both heat and carbon, less research has focused on the natural fluctuations of heat and carbon content associated with longer (decadal to centennial) time scales of variability.

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It is additionally important to examine heat and carbon variations together. A recent paper by Winton et al. (2013) showed that the impacts on heat and carbon uptake are different in response to changing ocean circulation. A change in ocean circulation has a larger influence on oceanic heat uptake than carbon uptake. This supports the results of Banks and Gregory (2006) and Xie and Vallis (2012), who show that temperature in the ocean does not in fact behave as a passive tracer.

While studies have focused on the forced response of oceanic heat and carbon and have demonstrated that heat and carbon have different storage and uptake patterns, we are unaware of any studies that have explored the unforced covariability of heat and carbon content. In this paper, we investigate natural variability of both heat and carbon content in multiple simulations of an Earth system model. We examine the magnitude and frequency of the variability in global heat and carbon content in simulations with various mesoscale mixing parameter settings. We then look more closely at the regional and spatial patterns of variability, and finally we propose possible mechanisms that drive this variability. Varying the mesoscale mixing parameters allows us to test the sensitivity of the patterns of variability and the mechanisms driving this variability. This analysis aims to help us understand the magnitude of natural variability and provide a context with which to view anthropogenic trends. Additionally it aids in the understanding of how carbon and heat vary with respect to each other.

Descriptions of the model used and quantities examined are found in section 2. Section 3 discusses the temporal and spatial variability in heat and carbon content. The mechanisms driving this variability are examined in section 4, and conclusions are in section 5.

2. Methods

a. Model and simulation descriptions

We use the GFDL ESM2Mc (Galbraith et al. 2011), a coarse-resolution configuration of the GFDL ESM2M (Dunne et al. 2012). The model has an atmospheric resolution of $3.875^\circ \times 3^\circ$ with 24 vertical levels. The ocean model is non-Boussinesq, using pressure as the vertical coordinate, and has a resolution of $3^\circ \times 1.5^\circ$ and 28 vertical levels. Despite its relatively coarse resolution, ESM2Mc has a realistic simulation of the southern annular mode (Galbraith et al. 2011), the response of Southern Hemisphere winds to an ozone hole (Seviour et al. 2017), and El Niño–Southern Oscillation (Russell and Gnanadesikan 2014). The vertical tracer diffusion coefficient (K_v) value is set within the KPP module. The value increases with depth and buoyancy forcing. When

the water column is statically unstable the value can exceed $4 \text{ m}^2 \text{ s}^{-2}$, which implies an equilibration time of approximately 5 days for a water column that is 4000 m deep. The oceanic model also has a coupled biogeochemical module referred to as the Biogeochemistry with Light Iron Nutrients and Gases (BLING) model (Galbraith et al. 2010). Although this module uses a highly parameterized biological cycle, it predicts patterns of carbon and oxygen change in response to global warming that are very similar to a more complex biogeochemistry simulation in ESM2M (Galbraith et al. 2015).

Because of the coarse resolution, processes associated with oceanic eddies are parameterized. The mesoscale advection of tracers along isopycnals is parameterized using the Gent–McWilliams parameterization scheme (Gent and McWilliams 1990). The diffusion coefficient, A_{GM} , varies spatially depending on the meridional gradient of the vertical shear between 100 and 2000 m. A default minimum and maximum value of A_{GM} is imposed at 200 and $1400 \text{ m}^2 \text{ s}^{-1}$ respectively. Additionally, the along-isopycnal diffusion (neutral diffusion) by mesoscale eddies is parameterized using a coordinate rotation method (Redi 1982). The neutral diffusion coefficient, A_{redi} , is set to a spatially constant value of $800 \text{ m}^2 \text{ s}^{-1}$ by default.

The model was initialized using the *World Ocean Atlas* present-day observations of temperature, salinity, and nutrients and was run for 1500 years with preindustrial (1860) values of greenhouse gases and aerosols. An additional 500 years were simulated using the default value of A_{redi} ($800 \text{ m}^2 \text{ s}^{-1}$) and this simulation is referenced as the *control* simulation. At year 1500, the model was branched to produce two more 500-yr simulations using different, constant values of $A_{\text{redi}} = 400$ and $2400 \text{ m}^2 \text{ s}^{-1}$. These runs are referred to as the *low eddy diffusion* and *high eddy diffusion* runs respectively. As discussed in Pradal and Gnanadesikan (2014) and Gnanadesikan et al. (2015), the value of A_{redi} varies significantly across modern climate models, which tend to use values lower than observational estimates (Ollitrault and Colin de Verdière 2002). The range of values used here is comparable to those seen in the CMIP5 model suite. One final 500-yr simulation was conducted by branching the control run and changing the minimum value of the mesoscale eddy advection coefficient, A_{GM} , to be $600 \text{ m}^2 \text{ s}^{-1}$ while maintaining the default value of A_{redi} ($800 \text{ m}^2 \text{ s}^{-1}$). This is referred to as the *high eddy advection* simulation.

Figure 1 shows the austral wintertime climatologies (JJA) for various Southern Hemisphere metrics with comparison to observations for all simulations. The Southern Ocean temperature (Fig. 1a) in the surface layer is biased warm for all simulations. Additionally, all simulations except the high eddy diffusion simulation have subsurface temperatures exceeding the observations. Similarly, the

FIG. 1. Comparison of control (blue), low eddy diffusion (purple), high eddy diffusion (red), and high eddy advection (green) simulations. JJA Southern Ocean (60° – 90° S) (a) temperature, (b) salinity, and (c) density stratification ($\sigma_0 - \sigma_0^{1500m}$); (d) JJA zonal surface wind stress; and (e) Antarctic sea ice extent. Observational data for each metric is shown in black. Temperature, salinity, and density stratification are estimates from the *World Ocean Atlas 2001* dataset (Stephens et al. 2002; Boyer et al. 2002). Surface wind stress values are from ERA-Interim and averaged between 1979 and 2015. Sea extent is calculated using the National Snow and Ice Data Center Sea Ice Index (Fetterer et al. 2016).

modeled surface salinity (Fig. 1b) is biased fresh for all simulations except the high eddy diffusion simulation. Figure 1c shows the profile of density stratification strength ($\sigma_0 - \sigma_0^{1500\text{m}}$). The model simulations envelop the observational density stratification with the high eddy advection simulation having the strongest density stratification and the high eddy diffusion simulation having the weakest stratification. The comparison of the modeled Southern Hemisphere westerly wind stress with the ERA-Interim westerly wind stress is shown in Fig. 1d. All the model simulations underestimate the strength of the wind stress south of 40°S and have an equatorward-biased peak in the wind stress. Finally comparison with the observational sea ice extent is shown in Fig. 1e. All simulations underestimate the sea ice extent in all months except the high eddy advection simulation, which has accurate sea ice extent values in the austral spring.

The various A_{redi} simulations are discussed at length in Pradal and Gnanadesikan (2014) and Gnanadesikan et al. (2015), which examine the mean climate response and sensitivity of anthropogenic carbon uptake to changing the A_{redi} parameter. Here instead, we use the various simulations to test the robustness of the mechanisms driving the covariability of heat and carbon. Because the different simulations have varying Weddell Sea convective variability (similar to the spread in CMIP5 models; see below), we can see if convection alters the mechanisms driving the covariability of heat and carbon in this model. Unlike the CMIP5 suite where differences in biological models, atmospheric radiation code, and sea ice formation contribute to intermodel spread, our simulations differ only in the mesoscale parameterizations to isolate the influence of Weddell Sea convection on the covariability of heat and carbon content.

b. Heat and carbon content

Heat and carbon content are calculated globally and regionally. The oceanic heat content (H) is calculated using the subsurface potential temperature (θ) and integrated globally:

$$H_{\text{global}} = \sum_{k=0}^{\text{bottom}} \sum_{j=-90}^{90} \sum_{i=0}^{360} \rho c_p \theta \delta x_i \delta y_j \delta z_k. \quad (1)$$

Similarly, carbon content is calculated using dissolved inorganic carbon (DIC) concentration and integrated globally:

$$C_{\text{global}} = \sum_{k=0}^{\text{bottom}} \sum_{j=-90}^{90} \sum_{i=0}^{360} \rho [\text{DIC}] \delta x_i \delta y_j \delta z_k. \quad (2)$$

Because the oceanic heat and carbon reservoirs are so large ($150,000 \times 10^{22}$ J and $37,000$ PgC, respectively),

and the natural variability relatively small ($\pm 3 \times 10^{22}$ J and ± 3 PgC, respectively), we express the variability as an anomaly from the climatological mean.

c. Surface heat flux

We determine the surface heat flux by vertically integrating the vertical diffusion term over the entire water column and subtracting the geothermal heat flux from the sea floor:

$$\sum_{k=0}^{\text{bottom}} \left[\rho_k c_p \left(\frac{\partial \theta}{\partial t} \right)_{\text{vdiff}} \right]_k \delta z_k - Q_{\text{geo}} = Q_{\text{SW}} + Q_{\text{LW}} + Q_{\text{latent}} + Q_{\text{sensible}} = Q_{\text{surface}}. \quad (3)$$

The advantage to defining the surface heat flux with this method, as opposed to the model-calculated surface heat flux, is that we can determine the heat lost to overlying sea ice in addition to the atmosphere as well as track heat sinks such as the melting of snow.

d. Southern Ocean

As has been previously documented (de Lavergne et al. 2014), ESM2Mc has a particularly active Southern Ocean. Deep convective events occur often in the Southern Ocean, and have a sizable impact on the climate system. Cabre et al. (2017) recently showed that Southern Ocean convective events in this model have an impact on the Southern Hemisphere surface temperatures, Hadley cell, and radiative balance. In light of the Southern Ocean influence in this model, we first assessed the contribution of Southern Ocean variability to global heat and carbon variability. Figure 2 shows the correlation between vertically integrated carbon (heat) content at each location with the global carbon (heat) content in the *control* simulation. This initial analysis suggests the importance of the Southern Ocean, and particularly the Weddell Sea, on global heat and carbon variability and will be more thoroughly examined in section 3.

3. Temporal and spatial variations in heat and carbon content

a. Weddell Sea convection

In the mid-1970s, an anomalous opening in the sea ice in the Weddell Sea was observed (Carsey 1980). Named the Weddell Polynya, this large opening was observed for three consecutive austral winters from 1974–76. The polynya was formed and maintained by vigorous convective mixing where the upward flux of deep and relatively warm waters provided enough energy to melt the overlying sea ice (Gordon 1982; Martinson et al. 1981).

FIG. 2. Correlation between (a) vertically integrated carbon content at each location and global carbon content and (b) vertically integrated heat content at each location and global heat content for the control simulation ($A_{\text{redi}} = 800 \text{ m s}^{-2}$).

This heat loss at the surface resulted in subsurface cooling deep into the water column, depleting the subsurface heat reservoir.

While a large feature like the Weddell Polynya has not been observed since and is considered to be a rare event, these polynya events can be quite common in climate models. A recent paper by [de Lavergne et al. \(2014\)](#) quantifies these convective events in CMIP5 model preindustrial control simulations and shows the spread across models. They find that some CMIP5 models have very little convection, while others have constant deep convection, with most models lying somewhere in between.

Changing the mesoscale eddy parameterization in our model suite has a large impact on the Weddell Sea deep convection. Figure 3 shows the annually averaged subsurface temperature as a function of time (colored contours) and the annual mixed layer depth (black line) averaged over the Weddell Sea (60° – 80°S , 60°W – 0°). The downward spikes in mixed layer depth and the concurrent decline in subsurface temperature indicate the occurrence of a deep convective event. The simulations range from no convection in the high eddy advection simulation (Fig. 3d) to constantly convecting in

FIG. 3. Annually averaged subsurface temperature (color contours) and mixed layer depth (solid black line) averaged over Weddell Sea for the (a) control simulation ($A_{\text{redi}} = 800 \text{ m s}^{-2}$), (b) low eddy diffusion simulation ($A_{\text{redi}} = 400 \text{ m s}^{-2}$), (c) high eddy diffusion simulation ($A_{\text{redi}} = 2400 \text{ m s}^{-2}$), and (d) high eddy advection simulation ($GM_{\text{min}} = 600 \text{ m s}^{-2}$).

the high eddy diffusion simulation (Fig. 3c), with the control and low eddy diffusion cases oscillating between convective and nonconvective periods (Figs. 3a,b).

When the neutral diffusion coefficient (A_{redi}) is increased as in the high eddy diffusion simulation, the along isopycnal diffusive mixing is increased. In the Southern Ocean where the isopycnals slope up to the surface and the subsurface water is warmer than the surface ocean, this increased along-isopycnal diffusion acts to decrease the vertical gradient in temperature and salinity (also shown in Figs. 1a–c). This results in a lower subsurface temperature, a weaker density contrast between deep and surface waters, less subsurface heat build-up, and no large convective “events” (Fig. 3c). Alternatively, a lower neutral diffusion coefficient as in the control and low eddy diffusion simulations does the opposite: the along-isopycnal diffusive mixing is decreased and subsurface heat is able to build up until a deep convective event occurs (Figs. 3a,b).

Changing the eddy advection coefficient (A_{GM}), on the other hand, impacts the slope of the isopycnal surfaces. As shown in [Gent et al. \(1995\)](#), increasing A_{GM}

acts to flatten the isopycnal surfaces and reduce vertical exchange. In the Southern Ocean where the isopycnals slope up to the surface, and the A_{GM} value is usually small, increasing the minimum value of A_{GM} thus reinforces the vertical density gradient. The result is a build-up of subsurface heat that continues to grow throughout the *high eddy advection* simulation. The reinforced density gradient is strong enough to suppress deep convection throughout the 500-yr simulation (Fig. 3d).

It is important to note that while the existence of subsurface heat build-up is known to be important for the existence of deep convective events, it is not yet known what mechanism initiates deep convection in the model or sets the time scales for convective variability. We have found, however, that by changing these parameterizations, we are able to span the range of convective variability seen in CMIP5 models as shown in de Lavergne et al. (2014) without the additional complications introduced by different representations of atmospheric processes and biological cycling. In this paper we will use these different convective states of the model to identify the impact convective variability has on both carbon and heat in the Southern Ocean and globally.

b. Global heat and carbon variability

We first aim to understand the variability in global oceanic heat and carbon content in the *control* simulation. The time series of global carbon and heat content anomaly is shown in Figs. 4a and 4b. Both quantities show strong multidecadal-scale variability, undergoing strong fluctuations roughly every 50 years. The magnitude of global carbon variability is about ± 3 PgC, which accounts for only approximately 3% of the estimated anthropogenic uptake of carbon over the past few decades (Khatiwala et al. 2012; Sabine et al. 2004; Waugh et al. 2006). The variability in global heat content on the other hand is about $\pm 3 \times 10^{22}$ J. This is a much larger percentage (20%) of the estimated uptake of anthropogenic in heat recent decades (Levitus et al. 2009). Figure 4c shows the time series of Weddell Sea (WS) subsurface temperature (averaged between 1500 and 2500 m). This quantity has been shown to be a good proxy for WS deep convection since the subsurface temperature is significantly decreased during convective events (Bernardello et al. 2014). Comparing the time series of the WS subsurface temperature to those of global heat and carbon anomalies, it is apparent that there is a strong relationship. In the control simulation, the WS subsurface temperature explains 61% and 35% (r^2) of the variance in global heat content and carbon content respectively (Table 1), with the strongest correlation occurring at time lag = 0. The correlation

FIG. 4. Carbon content anomaly, heat content anomaly, and Weddell Sea subsurface temperature (averaged over 1500–2000 m, 0° – 60° W, 60° – 80° S) for the control simulation. Blue circles indicate beginning of convection and red circles indicate end of convection defined using the four strongest local maxima and minima in Weddell Sea subsurface temperature.

between WS subsurface temperature and global heat and carbon content is also high for the low eddy diffusion simulation, while the relationship is less strong (yet significant) for the high eddy diffusion and high eddy advection simulations (Table 1). These results suggest that WS convection is closely tied to the global heat and carbon content.

The global heat and carbon content anomaly time series for all simulations is shown in Fig. 5. The magnitude and frequency of heat and carbon content variability changes substantially across the different simulations. Comparing the time series of global carbon content and heat content anomalies in the control simulation we find

TABLE 1. Relationship between Weddell Sea subsurface temperature and global carbon and heat content anomalies. All correlations are statistically significant from 0 ($p = 0.005$).

Simulation	Carbon content	Heat content
	Correlations (r)	
Control	0.59	−0.79
Low A_{redi}	0.61	−0.56
High A_{redi}	0.49	−0.20
High GM_{min}	0.12	−0.24

FIG. 5. Globally integrated carbon content anomaly (black) and heat content anomaly (red) for the (a) control ($A_{\text{redi}} = 800 \text{ m s}^{-2}$), (b) low eddy diffusion ($A_{\text{redi}} = 400 \text{ m s}^{-2}$), (c) high eddy diffusion ($A_{\text{redi}} = 2400 \text{ m s}^{-2}$), and (d) high eddy advection simulations ($GM_{\text{min}} = 600 \text{ m s}^{-2}$).

that they are anticorrelated ($r = -0.629$; Fig. 6). Given that in this model the global heat and carbon are primarily driven by Southern Ocean variability and Southern Ocean convection acts to deplete the Southern Ocean of both carbon and heat content, we would expect that global heat and carbon content should vary together. Therefore it is surprising that the two quantities are so strongly negatively correlated.

This anticorrelation relationship between global heat and carbon content is consistent in the additional simulations as well (Fig. 5). Figure 6 shows the Pearson correlation coefficient between global heat and carbon content for each simulation. All of the simulations have a statistically significant negative correlation between global heat and carbon exceeding -0.3 . The two simulations that oscillate between convective and non-convective periods (control and low eddy diffusion) have stronger correlations at or exceeding -0.5 . The fact that significant anticorrelation is found for all

FIG. 6. Pearson correlation coefficients for integrated carbon content anomaly vs integrated heat content anomaly for each region.

simulations suggests that the mechanisms causing this anticorrelation in global heat and carbon content are not strongly dependent on the convective state in the WS.

In light of these results, we find it helpful to divide these simulations up into two classes: the *low mixing simulations* that oscillate between convective and non-convective periods (control and low eddy diffusion) and the *high mixing simulations* that do not (high eddy diffusion and high eddy advection). The low mixing simulations are characterized by a build-up and subsequent release of abyssal heat content in the Southern Ocean (Fig. 3). These two simulations also have very strong oscillations in the global heat and carbon content, closely linked to the WS convection. The high mixing simulations, on the other hand, do not show this oscillation between subsurface build-up and release in the Southern Ocean, but rather either constant depletion in subsurface temperature in the high eddy diffusion (Fig. 3c) or a constant build-up of subsurface temperature in the high eddy advection (Fig. 3d). The lack of these oscillating convective states results in smaller global heat and carbon variability (Fig. 5), and a weaker relationship (although significant) between the WS and the global heat and carbon content.

To understand why the global heat and carbon are strongly anticorrelated, next we look at the regional relationships between heat and carbon content.

c. Regional heat and carbon variability

To diagnose which regions significantly contribute to the observed variability in global heat and carbon content, we break the global ocean into zonal bands: the Southern Ocean (90° – 55° S), the southern midlatitudes (55° – 20° S), the tropics (20° S– 20° N), the northern midlatitudes (20° – 60° N), and the Arctic (60° – 90° N). These

FIG. 7. Linear regression of each region's carbon content against global carbon content (blue) and each region's heat content against global heat content (red). Linear regression 95% confidence interval is shown but is too small to be discerned.

divisions were defined by the zonal average of the zero wind stress curl in order to isolate the dynamical regions (not shown). The correlation coefficients between heat and carbon content in each of these regions are also shown in Fig. 6. The correlation coefficients give a sense of what remains consistent across the simulations even with the different convective states. The Southern Ocean has a strong positive correlation between heat and carbon for all the simulations. Additionally, in the tropics there is a strong negative correlation between heat and carbon for all the simulations. This result suggests that the negative correlation in the tropics is key to understanding the negative correlation between heat and carbon seen globally.

To get a better sense of which regions dominate the variability, we decompose the global heat and carbon regionally by regressing the regional inventories of heat and carbon against the global inventories of heat and carbon. We first consider heat content in the control simulation (Fig. 7a, red dots). The regression highlights the importance of three regions in contributing to the global heat content signal: the Southern Ocean, southern midlatitudes, and tropics. The Southern Ocean regression coefficient has a magnitude similar to the southern midlatitudes and tropics, but the opposite sign. This indicates that the variability in Southern Ocean heat content is being

compensated by similar magnitude variability in heat content in both the southern midlatitudes and tropics.

The picture is nearly identical in the low eddy diffusion simulation (which also undergoes oscillations between convective and nonconvective states). The Southern Ocean heat content variability is compensated by similar magnitude variability in both the southern midlatitudes and tropics (Fig. 7b). However, the high mixing simulations are less clear. The regional heat content is dominated by the southern midlatitudes with weak compensation between the Southern Ocean and tropics (Figs. 7c,d).

The linear regression of regional carbon content (Fig. 7, blue dots), however, suggests that the Southern Ocean carbon content variability contributes most toward the global carbon content variability for all simulations. For the low mixing simulations, there appears to be compensation between the southern midlatitude and tropical carbon content variability. This compensation in regional variability is not seen in the high mixing simulations where the regression coefficients are both positive for these two regions. Regardless of these differences, the Southern Ocean is the region with the largest regression coefficient for all simulations.

The time series of the regional variability for heat and carbon content compared to the global heat and carbon

FIG. 8. Subsurface (a) potential temperature, (b) DIC, (c) remineralized DIC, and (d) preformed DIC for convective year composite from the control simulation. Only the surface ocean is shown to highlight the strongest-magnitude features.

content are shown in the supplemental information as an additional way to visualize the offsetting variations in different regions.

The subsurface spatial patterns further highlight the differences between the heat and carbon variability. Figures 8a and 8b show the subsurface potential temperature and dissolved inorganic carbon (DIC) for a convective composite of the *control* simulation. The convective composite is calculated by taking the four strongest local minimum values (and surrounding 6 years) in WS subsurface temperature and subtracting the four strongest local maximum values (and surrounding 6 years). The convective composite allows us to visualize the spatial patterns of variability after a convective event when the signal is strongest. The convective composite of both potential temperature and DIC show a strong decrease in the subsurface south of 60°S. This is consistent with deep WS convection mixing subsurface waters, high in heat content and DIC, to the surface and thus depleting the subsurface. Additionally, there is a strong warming of the surface waters throughout the Southern Hemisphere. This warming extends slightly into the subsurface in the midlatitudes, but the strongest warming is at the surface. The DIC convective composite (Fig. 8b) by contrast shows a decrease in the surface carbon throughout most of the Southern Hemisphere with an increase in the subsurface DIC in the midlatitudes.

4. Mechanisms driving variability

To understand why global heat and carbon content are anticorrelated we look more in depth at the

mechanisms driving the regional variability of these quantities.

a. Heat content variability

We first examine the variability of heat content. As shown for the control simulation subsurface temperature in Fig. 8a, convection acts to deplete the Southern Ocean of subsurface heat, and increase the surface heat content in the southern midlatitudes and tropics. These processes are more explicitly shown in Fig. 9. Periods of convection (highlighted in gray) are consistent with deepening of the mixed layer (black line), a depletion of subsurface Southern Ocean temperature (green line), an increase in Southern Ocean heat flux into the atmosphere (negative out of ocean; red line), and an increase in southern midlatitude and tropical SST (blue line). These processes are consistent in the low eddy diffusion simulation, which also oscillates between convective and nonconvective periods (not shown).

This relationship between WS deep convection and Southern Hemisphere surface warming is consistent with Bernardello et al. (2014) and Cabre et al. (2017). Both papers use the same GFDL model shown here in the control configuration to assess the impact of convection on the climate system and both sets of analysis show similar Southern Hemisphere surface warming in response to a convective event. Specifically, Cabre et al. (2017) show that during these wintertime convective events, substantial warming occurs in the Southern Ocean, increasing sea surface temperatures, decreasing sea ice and low clouds, and increasing solar radiation absorption. The result is a substantial warming of the Southern Hemisphere surface ocean and atmosphere. This atmospheric warming propagates to the rest of the

FIG. 9. (top) Weddell Sea subsurface temperature as in Fig. 4 (green) and Weddell Sea mixed layer depth (black). (bottom) Southern Ocean surface heat flux where positive indicates into the ocean (red) and Southern Hemisphere SST averaged between 0° and 55° S (blue) for the control simulation.

atmosphere almost instantaneously, changing the meridional temperature gradient and altering the strength of the Hadley cell in both hemispheres. For a more detailed look at the teleconnections between the Southern Ocean convection and tropical SST increases, we refer the reader to Cabre et al. (2017).

In this paper we show that the impact of this surface warming in the southern midlatitudes and tropics is strong enough to counteract the depletion of subsurface heat in the Southern Ocean, resulting in a global increase in heat content after WS convection.

b. Carbon content variability

Next we examine the regional mechanisms driving variability in carbon content in order to understand the anticorrelation between global heat and carbon content. Examining the control simulation (Fig. 8b), we see that during convection there is a strong subsurface depletion of DIC in the Southern Ocean, an increase in subsurface DIC in the southern midlatitudes, and a further depletion of surface-layer DIC in the southern midlatitudes to equator. To understand these spatial patterns, we break the DIC up into two components:

$$\text{DIC} = \text{DIC}_{\text{pre}} + \text{DIC}_{\text{remin}}, \quad (4)$$

where the preformed component (DIC_{pre}) is the DIC concentration of the water at the ocean surface and the remineralized component ($\text{DIC}_{\text{remin}}$) is the carbon concentration due to biological accumulation. Note that DIC_{pre} is set equal to DIC in the mixed layer and is advected and mixed into the ocean interior with biological

sources and sinks set to zero. Thus, by definition, $\text{DIC}_{\text{remin}}$ is zero within the mixed layer and represents the component of DIC in the interior that is due to biological sources and sinks.

When breaking the DIC down into its two components, we see that in the Southern Ocean there is a very strong depletion of subsurface remineralized carbon and a strong increase in preformed carbon (Figs. 8c,d). This signal is consistent with deep convective mixing. The increase in subsurface DIC_{pre} occurs from mixing relatively high surface DIC_{pre} down into the subsurface and the decrease in $\text{DIC}_{\text{remin}}$ occurs from mixing relatively high $\text{DIC}_{\text{remin}}$ from the subsurface to the surface layer. Mixing these high DIC waters from the abyssal Southern Ocean to the surface results in outgassing of CO_2 to the atmosphere (not shown) and the net result is a reduction in subsurface DIC.

The depletion in surface DIC in the Southern Hemisphere tropical region, on the other hand, is entirely due to a depletion in preformed DIC. This region also experiences a strong warming thus reducing the solubility of CO_2 within the surface waters and limiting the amount of DIC that can be held by the water in equilibrium with the atmosphere and at constant alkalinity. To verify that the reduction in solubility is driving the subsequent decrease in DIC, we show the DIC content versus heat content for the tropical region in Fig. 10a. The strong negative relationship supports the hypothesis that the variability in preformed DIC in this region is driven by changes in solubility. Figure 10a additionally shows the theoretical change in carbon content given a change in heat content due to solubility alone

FIG. 10. Scatter of heat content anomaly vs preformed DIC integrated over the tropical region for each simulation. Dashed gray linear line represents the linear fit of the carbon vs heat data with slope, m , and Pearson correlation coefficient r . Solid black linear line represents the projected change in carbon content given a change in heat content with constant alkalinity and $p\text{CO}_2$ in equilibrium with the preindustrial atmosphere [scaled from Gruber et al. (1996)].

(constant $p\text{CO}_2$ and alkalinity; black line) with a slope of $-0.27 \text{ PgC}/10^{22} \text{ J}$. This relationship is calculated using the relationship derived in Gruber et al. (1996) and scaled to relate carbon content with heat content. There is good agreement between this theoretical model and the linear regression of carbon content versus heat content for this region, represented by the dashed gray line (linear slope values m ; also shown in Fig. 10), further supporting the hypothesis that carbon variability is consistent with variability in solubility.

The above solubility mechanism appears to hold in all simulations (Figs. 10b–d). All simulations have the same negative relationship between preformed carbon content and heat content integrated over the tropical region (20°S – 20°N) with good agreement with the scaled solubility line (black line). This result suggests that the variability in DIC in this region is driven by variability in the temperature-driven solubility, regardless of the high-latitude convective variability.

Finally, we examine the southern midlatitude subsurface increase in DIC seen in Fig. 8b. Looking at the components of DIC, it is apparent that this increase is entirely due to remineralized DIC. To understand why this increase of remineralized DIC occurs, we correlate the remineralized DIC anomaly with ideal age in the southern midlatitude subsurface region (averaged between 40° and 50°S and 200–1000 m; Fig. 11). The ideal age is a tracer in the model simulation which quantifies

the mean time since the water last had contact with the surface. The tracer is set to zero in the mixed layer and ages at a rate of 1 yr yr^{-1} after it leaves the mixed layer. In all simulations, the remineralized DIC anomaly in this region is strongly correlated with ideal age with Pearson correlation coefficients exceeding 0.8 (Fig. 11). Calculating the linear regression coefficient (m) between the remineralized DIC and ideal age yields a rate of accumulation of remineralized DIC of approximately $0.25 \mu\text{mol kg}^{-1} \text{ yr}^{-1}$ for all simulations (Fig. 11). Comparing this rate of accumulation of remineralized DIC to the modeled local remineralization rate ($j\text{PO}_4 \times 108 = 1.6 \mu\text{mol kg}^{-1} \text{ yr}^{-1}$) we find that the rate of accumulation of remineralized DIC in this region is significantly less than the remineralization rate. The DIC found at a given point has accumulated along many trajectories, some largely passing through surface waters where the local remineralization rate is large, and some passing through deep waters where the local remineralization rate is small. The low slope of the relationship between $\text{DIC}_{\text{remin}}$ and age suggests that it is changes in the fraction of waters taking deeper trajectories that is most important in explaining the changes in Fig. 11.

Because only changes in transport cause the ideal age to change, the strong correlation between the remineralized DIC and ideal age suggest the accumulation of $\text{DIC}_{\text{remin}}$ is due to a slowdown of exchange between the surface and subsurface waters. This conclusion is only

FIG. 11. Ideal age vs remineralized DIC for all simulations. Quantities are averaged over 40° – 50°S and 200–1000 m. Linear regression coefficients m and Pearson correlation coefficients r are included for reference.

valid if the rate of local remineralization is constant or does not impact the time tendency of DIC in this region. Correlation analysis between the modeled remineralization rate and DIC tendency suggest no significant (or very small) correlation between the two variables (see Fig. S5 in the online supplemental information), indicating that the variability in subsurface $\text{DIC}_{\text{remin}}$ is indeed due to variability in transport.

To verify that the same spatial relationship of DIC and its components is consistent in all simulations, we show the covariance of globally integrated DIC against zonally (and vertically) integrated DIC, DIC_{pre} , and $\text{DIC}_{\text{remin}}$ in Fig. 12. The general pattern of covariance between the global DIC and remineralized DIC shows a strong positive value in the Southern Ocean followed by a decreasing to negative covariance in the southern

FIG. 12. Covariance between globally integrated DIC content and DIC (black), preformed DIC (blue), and remineralized DIC (red) for each simulation as a function of latitude. Note the different y-axis scales.

midlatitudes and then increasing again to above zero in the tropics. This pattern is apparent in all simulations, but with different magnitudes due to the different convective variability. When comparing with Fig. 8 it is important to note that these covariance calculations use the DIC integrated over the entire water column, whereas Fig. 8 only shows the surface layer (top 1500 dbars). Because of deep spreading of decreased $\text{DIC}_{\text{remin}}$ values from the Southern Ocean convection into the abyssal midlatitudes (see Fig. S6), the depth-integrated global DIC and remineralized DIC covariance does not become negative until approximately 45°S.

The opposite pattern holds for the covariance between global DIC and preformed DIC: a negative covariance in the Southern Ocean, followed by an increase in covariance in the southern midlatitudes and a decrease below zero north of the equator. Because of the lack of deep convection in the high mixing simulations, the Southern Ocean covariance is significantly smaller than the other simulations (note different y-axis scales in Fig. 12), but the qualitative relationship remains the same. The consistency in the general shape of these relationships suggests that the same mechanisms are controlling the regional variability in all simulations.

5. Conclusions

Using a coupled climate model, we have quantified the global and regional natural variability in oceanic heat and carbon content. We have found that in this model, the highly convective Southern Ocean drives strong global variability in heat and carbon content. Additionally, these two quantities are strongly anticorrelated. Using simulations with different parameter settings for mesoscale mixing, we show that these results are robust across simulations with different WS convective variability, but the anticorrelation relationship is strongest with the two simulations that oscillate between convecting and nonconvecting states.

As illustrated in Fig. 13, the global anticorrelation between heat and carbon content is due to differences in the sign and magnitude of the regional variability. The arrows in the schematic indicate the magnitude of variability and the sign during a convective period. As indicated, the global heat and carbon content are anticorrelated.

In the Southern Ocean, heat and carbon content are both depleted during convection, but the southern midlatitude and tropical regions each have heat content variability that balance the Southern Ocean variability. The resulting global heat content variability therefore has the same sign and magnitude as the variability in the southern midlatitudes and tropics. Carbon content

variability, on the other hand, exhibits a cancellation between the southern midlatitudes and tropics. Therefore, the resulting variability in global carbon content closely follows the variability in the Southern Ocean.

The subsurface variability structure is also depicted in Fig. 13 and highlights the differences between heat and carbon. During convection, both quantities decrease in the subsurface Southern Ocean. Additionally, both heat and carbon show increases in the southern midlatitudes, but the temperature increases are contained in the surface, while DIC increases at depth. This increase in subsurface DIC is likely a result of decreased ventilation. Finally, the southern midlatitudes and tropics show an increase in surface temperature and a decrease in surface DIC. The variability in DIC here is due to solubility decreases as a result of the temperature increase.

Comparing the magnitude of the modeled natural variability to the size of recent observed trends can provide information on how detectible anthropogenic trends are (Thomas et al. 2015). For the control simulations, the magnitude of global carbon variability is about $\pm 3 \text{ PgC}$. This accounts for approximately 3% of the estimated anthropogenic uptake of carbon over the past few decades (Khaliwala et al. 2012; Sabine et al. 2004; Waugh et al. 2006). The variability in global heat content on the other hand is about $\pm 3 \times 10^{22} \text{ J}$. This is a much larger percentage (20%) of the estimated uptake of anthropogenic heat in recent decades (Levitus et al. 2009). These results suggest that changes in carbon content due to anthropogenic activity are unlikely to be obscured by long-time scale variability, but changes in heat content could be obscured. This large natural variability in global heat content could explain why there is less CMIP5 model agreement in oceanic heat uptake than there is for carbon uptake (Frölicher et al. 2009).

If we assume these results hold for the real ocean, we would expect that during the current nonconvective period we would experience a subsurface warming in the Southern Ocean and a slowdown of the intermediate water ventilation. Both these processes have been documented in observational studies (Purkey and Johnson 2012; Waugh et al. 2013), but it is important to note that these changes could also be due to anthropogenic influences such as greenhouse gas warming and ozone depletion in addition to variability in WS convection. The frequency of modeled WS convection is a hard to compare to real-life WS convection because of the lack of an observational record in the Southern Ocean. Additionally, de Lavergne et al. (2014) have shown that models that have frequent convection in preindustrial control simulations have a significant reduction in convection under global warming scenarios. This suggests that we may not observe another strong

FIG. 13. Schematic summarizing regional variability in oceanic heat and carbon during a convective year. Arrows designate the sense of global and regional inventory change during a convective year (positive indicating an increase in oceanic content).

WS convective event, and makes it extremely difficult to determine what frequency of WS convection is “correct.”

The results of this study suggest that the atmosphere could exhibit significant changes in temperature and CO_2 concentration in response to Southern Ocean convective variability. A previous study by Cabre et al. (2017) using our control version of the ESM2Mc model shows an increase in SH and global atmospheric temperatures. This is because the additional flux of heat into the ocean is more than balanced (and indeed is driven) by a decrease in clouds and ice, resulting in an additional 0.15 PW of additional shortwave heating of the Southern Hemisphere when convection is at its peak. An interesting extension of this study would be to examine whether relatively small preindustrial changes in atmospheric carbon dioxide could be associated with changes in SH temperatures, as well as a more comprehensive examination of this process in Earth system models with variable atmospheric carbon dioxide.

A caveat with this study is that only a single model has been used. More analysis should be conducted with additional model simulations to examine if this relationship and the relative magnitudes of variability between heat and carbon are consistent. Similar analysis with additional models could help to understand the intermodel spread of oceanic carbon content, and the larger intermodel spread in oceanic heat content (Frölicher et al. 2014), and also provide a better context in which to analyze recent observational trends. Additionally, the model used in this analysis has a relatively coarse resolution and parameterizations for mesoscale eddies. Dufour et al. (2017) assessed the impact that model resolution has on WS convection and concluded that horizontal model resolution has an important impact on vertical stratification and the subsurface heat reservoir build-up. However, the impact of resolution is not straightforward: a $1/4^\circ$ ocean behaved more like our high eddy diffusion model with relatively constant

convection while a $1/10^\circ$ ocean model showed more stratification and behaved more like our control model. Griffies et al. (2015) have additionally examined the impact eddies have on Southern Ocean heat uptake and transport in eddy-permitting models and have concluded that uncertain model parameterizations tend to lead to model drift and less accurate lateral and vertical heat distribution. These impacts need to be kept in mind when discussing model simulations with parameterized eddies.

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