The Atlantic Meridional Heat Transport at 26.5°N and Its Relationship with the MOC in the RAPID Array and the GFDL and NCAR Coupled Models

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ABSTRACT

The link at 26.5°N between the Atlantic meridional heat transport (MHT) and the Atlantic meridional overturning circulation (MOC) is investigated in two climate models, the GFDL Climate Model version 2.1 (CM2.1) and the NCAR Community Climate System Model version 4 (CCSM4), and compared with the recent observational estimates from the Rapid Climate Change–Meridional Overturning Circulation and Heatflux Array (RAPID–MOCHA) array. Despite a stronger-than-observed MOC magnitude, both models underestimate the mean MHT at 26.5°N because of an overly diffuse thermocline. Biases result from errors in both overturning and gyre components of the MHT. The observed linear relationship between MHT and MOC at 26.5°N is realistically simulated by the two models and is mainly due to the overturning component of the MHT. Fluctuations in overturning MHT are dominated by Ekman transport variability in CM2.1 and CCSM4, whereas barotropic geostrophic transport variability plays a larger role in RAPID. CCSM4, which has a parameterization of Nordic Sea overflows and thus a more realistic North Atlantic Deep Water (NADW) penetration, shows smaller biases in the overturning heat transport than CM2.1 owing to deeper NADW at colder temperatures. The horizonal gyre heat transport and its sensitivity to the MOC are poorly represented in both models. The wind-driven gyre heat transport is northward in observations at 26.5°N, whereas it is weakly southward in both models, reducing the total MHT. This study emphasizes model biases that are responsible for the too-weak MHT, particularly at the western boundary. The use of direct MHT observations through RAPID allows for identification of the source of the too-weak MHT in the two models, a bias shared by a number of Coupled Model Intercomparison Project phase 5 (CMIP5) coupled models.

1. Introduction

The Atlantic Ocean provides a significant contribution to the global oceanic heat transport through its meridional overturning circulation (MOC). The oceanic heat transport has been estimated both directly, from hydrographic observations across transbasin sections, and indirectly, from the residual of atmospheric observations and satellite measurements of top of the atmosphere radiation. Estimates of the time-mean Atlantic Ocean meridional heat transport (MHT) from single hydrographic sections between 24° and 26°N and from multiple sections combined with inverse models range between 1.1 and 1.4 PW (1 PW = 10^15 W), with an uncertainty of about 0.3 PW (Hall and Bryden 1982; Lavin et al. 1998; Ganachaud and Wunsch 2003; Lumpkin and Speer 2007). Indirect measurements yield consistent estimates, albeit with slightly smaller values ranging

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between 0.85 and 1.15 PW around 26.5°N, and with a larger uncertainty than direct estimates (Trenberth et al. 2001; Bryden and Imawaki 2001; Trenberth and Fasullo 2008). Quantifying the MHT in climate models and comparing the simulated values with the best observational estimates is a common test to evaluate coupled models.

Recently, direct and continuous measurements of Atlantic MHT have become available through the Rapid Climate Change–Meridional Overturning Circulation and Heatflux Array (RAPID–MOCHA) observing system, deployed since 2004 to continuously monitor the MOC at 26.5°N (Cunningham et al. 2007; Kanzow et al. 2007, 2008). The MHT estimates derived from the RAPID array have been described by Johns et al. (2011). They showed that the time-mean MHT at 26.5°N averaged over the first 3.5 years of deployment equals 1.33 PW and has a standard deviation of 0.40 PW. The mean is slightly higher than in previous estimates but the uncertainty is smaller, with an error of ±0.14 PW, including statistical uncertainty related to MHT fluctuations and bias uncertainty resulting from measurement errors (Johns et al. 2011). Understanding what controls the variability of the Atlantic MHT and how that relates to the MOC is highly important to better identify and potentially predict its future behavior. Model simulations indicate a decrease of the MOC strength under increased greenhouse gas emissions (Pachauri and Reisinger 2007). In the RAPID array observations a linear relationship was identified between MOC and MHT at 26.5°N, with a regression slope of 0.079 PW Sv⁻¹ (1 Sv = 10⁶ m³ s⁻¹) (Johns et al. 2011). Given that relationship, the MHT is expected to decrease along with the MOC transport in response to increased greenhouse gases, unless it is compensated by other contributions like the horizontal circulation or the eddy-induced heat transport (Drijfhout and Hazeleger 2006) or if the mechanisms that link MOC to MHT differ on interannual and climate-change time scales.

Because future climate changes can only be assessed from coupled models, it is crucial to identify the importance of each contribution to the MHT and assess how realistically they are reproduced in the coupled models that are used in the climate prediction efforts. Evaluation and description of the simulated ocean heat transport in the Atlantic have been done in previous studies. Jia (2003) described the representation of global MHT in several coupled models that were part of the Coupled Model Intercomparison Project (CMIP) phases 1 and 2 (CMIP1 and CMIP2) experiments. This analysis showed that most coupled models underestimate the total MHT and reproduce the linear relationship between MOC and MHT, but with a smaller regression coefficient than observed. Model systematic biases, defined by the departure from observations, were suggested to be the main source of discrepancy, in particular errors in the formation and export of North Atlantic Deep Water (NADW). The analysis of high-resolution forced ocean general circulation models led to similar results (Bönig et al. 2001; Biastoch et al. 2008). Previous modeling and observational studies also suggested that the Atlantic MHT was primarily attributable to the MOC, with little contribution from the horizontal circulation. However, continuous measurement of the overturning and horizontal mass and heat transports were not available at that time to assess the realism of model results and the robustness of observational estimates. The completion of more recent model simulations and the availability of newer observational estimates from the RAPID array make it an appropriate time to review the progress and reassess the estimation of Atlantic Ocean heat transport in climate models. In ocean and coupled models there is, in general, a nonzero mass transport through a given section, which can be a problem in diagnosing the heat transport since a mass balance is required to eliminate arbitrary state constraints. A meaningful comparison with observations should thus also be based on quantities that are directly comparable, as recommended by Bryden and Imawaki (2001).

The seasonal to interannual variability of the MHT in the subtropics has been shown to be mainly associated with the wind-driven Ekman transport (Bönig et al. 2001). Jayne and Marotzke (2001) described the ocean heat transport as a compensation between an Ekman transport associated with wind stress and a barotropic geostrophic transport due to zonal pressure gradient. Recent analysis of RAPID data suggested a larger influence of baroclinic geostrophic variability than was previously assumed, even on annual and shorter time scales (Johns et al. 2011). This geostrophic variability might be underestimated in coupled models (Sarojini et al. 2011), although the source of discrepancy remains unclear as it has not been fully investigated yet.

The aim of this study is to revisit the MHT–MOC relationship using newer observations and newer, likely more realistic climate models, namely, the Geophysical Fluid Dynamics Laboratory (GFDL) Climate Model version 2.1 (CM2.1) and the National Center for Atmospheric Research (NCAR) Community Climate System Model version 4 (CCSM4). We investigate how well the two coupled models reproduce the observed Atlantic oceanic heat transport at 26.5°N, near the latitude of the observed maximum transport. Of the two coupled models used here, only NCAR CCSM4 includes a parameterization of Nordic Seas overflows (Danabasoglu et al. 2010), yielding a more realistic representation of NADW. This
allows us to test the sensitivity of the MHT estimate to the representation of the NADW cell. Section 2 briefly describes the coupled model simulations and the RAPID data used in this study. In section 3, we describe the mean MHT and the mean MOC and investigate the sensitivity of MHT variability to MOC changes at 26.5°N. We assess the contribution of the overturning and horizontal components and compare model results with RAPID. We address the main causes of discrepancies between models and between models and observations in section 4 by looking at the sensitivity of the overturning heat transport to Ekman and baroclinic geostrophic variability. Conclusions and discussion are given in section 5.

2. Description of models and observational data
   a. The RAPID–MOCHA array

   The RAPID–MOCHA array has been deployed since April 2004 to continuously monitor the MOC at 26.5°N. The mooring array measures full water-column profiles of density and bottom pressure at the western and eastern boundaries of the basin at 26.5°N. The density difference between the western and eastern endpoints allows for the computation of the zonally integrated geostrophic profile of the meridional flow across 26.5°N. The detailed methodology for estimating the MOC from its different components is described in Cunningham et al. (2007) and Kanzow et al. (2007, 2008). The data used here are derived from the first 3.5 years of deployment (from April 2004 to October 2007) and are based on 10-day averages, as described in Johns et al. (2011). The continuous RAPID array measurements give better estimates of the mean and variability of the MHT than one-time hydrographic sections, as the array captures the long-term mean conditions and variance more accurately.

   b. The GFDL CM2.1

   The GFDL model used here is the CM2.1 version that was used for the CMIP3 (Delworth et al. 2006) and which is also part of the CMIP5 experiments. The grid spacing of the atmospheric component is 2° latitude × 2.5° longitude. The ocean grid spacing is a nominal 1° in longitude and latitude with reduced latitudinal spacing down to 1/16 toward the equator. Detailed description of the model mean state and variability can be found in Delworth et al. (2006) and Gnanadesikan et al. (2006). We use monthly mean outputs from a preindustrial control simulation in which the concentration of greenhouse gases is held fixed at 1860 values.

   c. The NCAR CCSM4

   The model used in this study is version 4 of the NCAR Community Climate System Model and is used for CMIP5 and described in Gent et al. (2011). The atmospheric component has a nominal resolution of about 1°. The ocean component uses 60 vertical layers and has a horizontal resolution of nominally 1° increasing to 0.27° near the equator (Danabasoglu et al. 2012). The ocean model includes a new parameterization described in Danabasoglu et al. (2010) that represents gravity current overflows such as Denmark Strait and the Faroe Bank Channel overflows from the Nordic Seas. As shown by Danabasoglu et al. (2010) and Yeager and Danabasoglu (2012), this leads to a better representation of the NADW and, thus, of the MOC.

   d. Analysis period

   To have a good estimate of the long-term mean, the model mean state is evaluated using monthly mean outputs from a 50-yr segment of the corresponding control simulation (years 1200–49 with 1850 conditions for CCSM4, years 901–950 with 1860 conditions for CM2.1). As shown in appendix A, the results do not depend on the choice of simulation length and are robust when using a different sampling. While our main analysis is based on the preindustrial simulation, we also make use, for both CM2.1 and CCSM4, of a 300-yr present-day control run in which CO2 concentrations are fixed at 1990 values and an ensemble of 140-yr historical simulations (1861–2000) that include all twentieth-century forcings. A 50-yr segment is considered for the former control run, and the whole length of the simulation for the latter.

3. Link between the Atlantic MHT and MOC
   a. Atlantic heat transport in the coupled models and observational estimates

   The mean Atlantic oceanic heat transport as simulated by the CM2.1 and the CCSM4 models under preindustrial conditions is shown in Fig. 1 in comparison with the available direct and indirect observational estimates. The magnitude of the simulated and observed transport is positive at all latitudes, consistent with heat being carried northward in both hemispheres of the Atlantic Ocean. Although the latitudinal variation of the heat transport is broadly consistent across the different estimates, there are significant differences in the magnitude, with generally larger values in direct estimates than in indirect estimates. As pointed out by Bryden and Imawaki (2001) and Johns et al. (2011), the latter also have larger uncertainties because they are derived by subtracting the atmospheric heat transport from the top-of-the-atmosphere (TOA) radiation data from the Earth Radiation Budget Experiment (ERBE). The location of the maximum transport is data dependent. It is close to 15°N in the National Centers for Environmental
Prediction (NCEP) and European Centre for Medium-Range Weather Forecasts (ECMWF) estimates of Trenberth et al. (2001), while it is more widely distributed between 20° and 30°N in the more recent estimates of Trenberth and Fasullo (2008), and it peaks around 22°8 in the Large and Yeager (2009) estimates. Note that the ocean heat transport by Large and Yeager (2009) is not computed as a residual from TOA and atmospheric heat transport but is based on best estimates of air–sea heat flux, assuming no net ocean heat storage. In the direct observations by Ganachaud and Wunsch (2003), the MHT peaks around 24°8N and is larger than in all other estimates, except RAPID, at 26.5°8N, which shows the largest value and the smallest error bar. The Atlantic MHT from the coupled models lies mostly in the range of these different estimates. CCSM4 values peak around 17°8N, reaching 1.19 PW, with a meridional distribution very close to the Large and Yeager (2009) reanalysis. The MHT maximum in CM2.1 is smaller than that in CCSM4 and RAPID, but above the Trenberth and Fasullo (2008) and ECMWF estimates, with a maximum of 1.12 PW located around 16°N.

We focus on 26.5°N latitude for the remainder of the paper because this is where the RAPID array is located. Hereafter, MHT will refer to the Atlantic oceanic heat transport at 26.5°N, keeping in mind that it differs from the maximum heat transport in the two models considered here. We define the total MHT across the 26.5°N horizontal section by

\[ Q = \rho_0 C_p \int_0^L \int_{-H}^0 \nu T \, dz \, dx, \]  

(1)

where \( \rho_0 \) is the seawater density, \( C_p \) is the specific heat capacity of seawater, and the product \( \rho_0 C_p \) is nearly constant in the ocean (±1%) with a mean value of 4.1 × 10^6 J m^-3 °C^-1 used here; \( \nu \) is the Eulerian-mean meridional velocity, \( T \) is the potential temperature, and \( H \) and \( L \) are the depth and width of the ocean, respectively. The MOC is defined here as the maximum of the overturning streamfunction: \( \Psi(z) = \int_0^L \int_{-H}^0 \nu(x, z) \, dz \, dx \). The MHT and MOC values in both models and observations are based on a zero net volume transport across the section. Indeed, in observations the geostrophic
velocity estimates depend on the choice of a zero velocity reference, and very small changes in the reference velocity can lead to very large differences in the interior circulation, which can alter significantly the resulting heat transport estimates (Bryden and Imawaki 2001). Diagnosing the heat transport thus requires a zero net mass transport through the section to eliminate arbitrary state constraints. In the models there is, in general, a nonzero mass transport through a given section. At 26.5°N there is an actual southward net transport of about 1.0 Sv through the basin, resulting from the Bering Strait inflow, and its effect needs to be considered to define a mass-conserving heat transport. Following Bryden and Imawaki (2001), the basin-averaged velocity (at 26.5°N from coast to coast and for full depth) is removed from the full velocity field before calculating the MHT, such that the resulting MHT values are associated with zero net mass transport and are therefore independent of temperature reference. Given that the MHT in the Atlantic is dominated by Eulerian flow, the model MHT described in this study does not consider the parameterized eddy contribution, which was found to be small at this latitude in observations (Johns et al. 2011) and in the two coupled models. Indeed, the model parameterized eddy flux is negligible at 26.5°N, as it accounts for about 0.2% ± 0.1% of the total mean transport in CM2.1 and 0.6% ± 0.1% in CCSM4 when estimated over 3.5-yr segments of the 50-yr control simulation. The RAPID array MHT estimate equals 1.33 PW with an error bar of ±0.14 PW (Johns et al. 2011), which is close to the Ganachaud and Wunsch (2003) estimate of 1.27 ± 0.15 PW at 24°N. The error bar in the RAPID estimate includes the uncertainty arising from the individual components of the transport associated with the MHT (Florida Current transport, Ekman transport, and midocean transport), which are combined randomly and statistically averaged over the length of the record to account for MHT intrinsic variability. This yields an error bar of 0.07 PW. Added to this is the error resulting from the measurement system for each transport component, which is estimated to be 0.07 PW. The sum of the two errors gives a total uncertainty of 0.14 PW. Details about the calculation of this uncertainty are given in Johns et al. (2011).

The mean MHT at 26.5°N in the preindustrial simulations of CM2.1 and CCSM4 equals 1.05 and 1.18 PW, respectively. The CCSM4 value is the same as the NCEP and Large and Yeager (2009) indirect estimates, while the CM2.1 value falls within the range of the 1-σ upper value of Trenberth and Fasullo (2008). Computing the MHT at 26.5°N using the online model calculations (which do not remove the basinwide net transport) gives comparable values, with a mean transport of 1.01 ± 0.01 PW in the preindustrial CM2.1 control run and 1.14 ± 0.01 PW in CCSM4, where the error bar is defined by the standard deviation of the MHT over 50-yr-long segments spanning the multicentury control simulation. This standard deviation increases to 0.05 PW in CM2.1 and 0.03 PW in CCSM4 when 3.5-yr segments are used instead, with the mean MHT remaining the same. The computation of the offline MHT from monthly mean outputs falls therefore within this range of variability, and we assume in the following that the error resulting from the use of monthly means is negligible. Using the MHT from present-day and historical runs yields mean MHT values that are very similar to the preindustrial simulation estimates and lying within the models error bars shown in Fig. 1. Even when considering model maximum transports across latitudes instead of the one at 26.5°N, the simulated MHT never reaches RAPID estimates. This suggests that both coupled models underestimates the Atlantic MHT.

b. Mean MOC in CM2.1, CCSM4, and RAPID

Observational studies by Roemmich and Wunsch (1985) and Bryden (1993) showed that the MOC is the main contributor to the northward heat transport in the Atlantic, with a smaller additional contribution from the horizontal circulation. This suggests that an underestimation of the MOC volume and heat transports could be the source of the model MHT discrepancy compared with observations. Figure 2 shows the North Atlantic mean MOC simulated by CM2.1 and CCSM4 in the preindustrial simulations. The NADW cell is characterized by a northward flow in the upper 1000 m and a southward flow below. The NADW penetrates deeper in the CCSM4 simulation owing to the overflow parameterization (Danabasoglu et al. 2012). Consequently, the Antarctic Bottom Water (AABW) cell reaches 4 Sv in CM2.1 and is weaker in CCSM4. The maximum of the streamfunction equals 22 Sv in CM2.1 and 24 Sv in CCSM4 and is located around 1000-m depth in both models, at about 40°N in CM2.1 and 35°N in CCSM4. The reason for a localized maximum at 35°N in CCSM4 has been suggested to result from a much reduced viscosity in this model version, as discussed by Yeager and Danabasoglu (2012). Present observations alone cannot provide such a large-scale integrated representation of the basinwide MOC, but the MOC profile can be derived from the RAPID array data, as shown in Fig. 3. The observed streamfunction profile increases to a maximum of 18.5 Sv at 1100 m and decreases below. The shape of the upper-ocean MOC profile is quite well simulated in CCSM4, despite a slightly too-strong maximum transport of 19 Sv. The magnitude of the maximum transport is even larger in CM2.1, with a value slightly exceeding
Although only preindustrial values are shown here, the magnitude of the MOC maximum is actually closer to observations in the present-day and historical simulations, probably in part because of warmer conditions than under preindustrial forcing. We choose to focus on the preindustrial simulations in the rest of this study because they have been run longer, allowing a better adjustment of the MOC at depth and a more accurate estimate of the mean state. Note, however, that the analysis was also conducted for the present-day and historical simulations, leading to comparable outcomes.

The comparison of the simulated MOC profile with observations is not as good below 2000 m. In both models the southward NADW flow that balances the northward upper-ocean flow is too shallow, as evidenced by the deeper zero crossing in Fig. 3 in RAPID. The NADW flow extends to 3000 m in CM2.1 and 3600 m in CCSM4 compared to about 4300 m in observations. The remaining flow below these depths is associated with vertical recirculation of AABW. The northward AABW flow occurs below 5000 m in observations, while it occurs below about 3800 m in CM2.1 and is near zero in CCSM4 at this particular latitude (Danabasoglu et al. 2012). Most of the heat transport carried by the overturning circulation is associated with the upper-ocean cell because of the large temperature difference between the near-surface waters and NADW. The corresponding profiles of zonal-mean temperature for the models and observations are shown in Fig. 3. A misrepresentation of the vertical structure of the NADW flow can lead to a significant bias in the associated heat transport since it can affect the average temperature difference between the upper and lower branches of this cell, as will be discussed later. Figure 3 shows that CM2.1 and CCSM4 realistically simulate the zonal-mean temperature distribution in the upper 500 m but show a pronounced warm bias below, strongest in CM2.1. Despite the overflow parameterization and a more realistic NADW cell magnitude and depth, CCSM4 is still too warm around 1000 m but is in better agreement with observations at depth below 1800 m, suggesting a better representation of lower NADW.

c. Relationship between mean MHT and MOC and their variability at 26.5°N

As shown in section 3a, the MHT at 26.5°N equals 1.05 PW in CM2.1 and 1.18 PW in CCSM4, giving values below RAPID mean estimates by 21% and 11%, respectively (Table 1), despite a stronger-than-observed maximum MOC in both models. Thus, the MOC strength is not the source of the low bias in the models. To better understand the source of the bias, it is useful to break the heat transport into overturning and horizontal components (e.g., Bryan 1982):

\[
Q = Q_{ov} + Q_{gyre} = \rho_0 C_p \left[ \overline{\bar{v}\bar{T}} dz dx + \rho_0 C_p \left( \int \bar{\nu}' T' dz dx \right) \right],
\]

where overbars represent the zonal average corresponding to the overturning component \(Q_{ov}\) and primes represent the deviations from the zonal mean that define the horizontal transport associated with the large-scale gyre circulation \(Q_{gyre}\). Both \(Q_{ov}\) and \(Q_{gyre}\) conserve mass by definition and, hence, contribute directly to the total MHT (Bryden and Imawaki 2001). The overturning circulation in RAPID accounts for 90% of the total MHT with a mean value of 1.18 PW. The corresponding values in CM2.1 and CCSM4 are 1.08 and 1.19 PW, respectively, which slightly exceeds the total MHT value in both models (Table 1). The mean value of \(Q_{ov}\) is comparable to observations in CCSM4 but too
small in CM2.1 by about 0.1 PW. The mean gyre heat transport that is northward in RAPID is weakly southward in both models, decreasing the total northward MHT in the models. This suggests that, although dominated by the overturning component, the total mean MHT is underestimated in CM2.1 (partly) and CCSM4 (mainly) because of biases in the horizontal component of the heat transport.

In addition to these mean biases, it is instructive to consider the sensitivity of the MHT fluctuations about its time mean value to the corresponding fluctuations in the MOC strength. Regressing the observed total MHT onto the MOC indicates a linear relationship between mass and heat transports at 26.5°N that is found in the two coupled models as well (Fig. 4). The observed slope of 0.079 PW Sv−1 is rather well reproduced in CM2.1 but underestimated in CCSM4. Both models show some sensitivity to the external forcing but have very similar values under preindustrial, present-day, and historical conditions, as shown in Fig. 4. On average, the slope between the total MHT and the MOC at 26.5°N is around 0.08 PW Sv−1 in CM2.1 and closer to 0.07 PW Sv−1 in CCSM4. In both models results are shifted toward a lower MHT than in observations for a given MOC transport. However, in CM2.1 this offset remains independent of MOC strength (since the sensitivity is correct), while in CCSM4 it increases with MOC strength because the sensitivity is too low. This relationship does not depend

<table>
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<th>Model</th>
<th>$\Psi_{\text{max}}$ (Sv)</th>
<th>$Q$ (PW)</th>
<th>$Q_{\text{ov}}$ (PW)</th>
<th>$Q_{\text{Ek}}$ (PW)</th>
<th>$Q_{\text{geo}}$ (PW)</th>
<th>$Q_{\text{gyre}}$ (PW)</th>
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</tr>
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<td>-0.01</td>
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</table>
on the different sampling between observations and models outputs, as shown in appendix A. Regressing $Q_{ov}$ onto the MOC indicates that the sensitivity of MHT variability to the MOC is mainly due to the overturning component, with a slope comparable with observations in both CM2.1 and CCSM4 (Figs. 4c,d). Compared with the regression on the total MHT, the slope has increased in both models but decreased in observations. This is because the gyre component of the MHT shows a small negative slope when regressed onto the MOC, whereas in observations the slope is positive. For practical purposes, however, $Q_{gyre}$ is nearly independent of the MOC strength in both models and observations. In the following sections, we seek to understand the source of the bias in $Q_{gyre}$ in both models, as well as the low bias in $Q_{ov}$ in CM2.1. We also consider why, for example, the sensitivity of the MHT to the MOC fluctuations is approximately correct in CM2.1, even though it has a significant low bias in the mean $Q_{gyre}$.

4. Assessing the source of discrepancies between models and observations

a. The overturning heat transport

We first investigate the source of the bias in the overturning heat transport, as it is the dominant contribution to the total MHT in both models and observations. Figure 3 highlighted significant temperature biases in the two models compared with observations. To better
identify where the bias in the zonal-mean temperature arises, the observed mean potential temperature along 26.5°N is shown in Fig. 5, along with the corresponding bias in the two coupled models. Observed data are derived from the 1998 World Ocean Atlas dataset (hereafter WOA) described by Levitus et al. (1998). The mean potential temperature shows a downward tilt of the thermocline from east to west and a more diffuse lower thermocline in the east, characteristic of the subtropical distribution. Taking the difference with the models shows that both CM2.1 and CCSM4 have a warm bias at depth, slightly larger in CM2.1, that extends across the whole basin from about 800 to 1500 m depth and shoals to the east. Above 800-m depth both models are too cold compared with observations, with a much larger bias in CM2.1 than in CCSM4. This is primarily due to an overall too-diffuse thermocline in the models compared to observations, as can be seen in Fig. 3. The tilt of the thermocline across the basin also tends to be underestimated in coupled models at this resolution, which accounts for the zonal asymmetries in the bias. Note that the distribution of the subsurface potential temperature bias across the basin is partially compensated when taking the zonal mean, particularly in CCSM4.

The temperature biases described above can have a significant influence on the overturning heat transport. Figure 6 shows the vertical distribution of the cumulative potential temperature transport in RAPID, CM2.1, and CCSM4. By definition, for each profile the temperature transport values sum up vertically to give, once at the bottom, a heat transport equal to the total MHT in Fig. 6a and to the overturning heat transport $Q_{ov}$ in
The simulated profiles are comparable to observations but are biased toward lower values of total and overturning transports for both models. The bias in the total transport is quite similar in the two models in the upper 500 m, but gets larger in CM2.1 as depth increases, leading to a smaller total MHT in CM2.1 than in CCSM4, as presented earlier in this study. The profiles of the overturning component show a very realistic distribution in CCSM4 but a too-small transport in CM2.1. The overturning bias in CM2.1 appears at about 1000 m and increases down to 3000 m, under which depth it remains constant to give a $Q_{ov}$ of 1.08 PW in CM2.1 instead of the observed 1.18 PW. CCSM4 has a mean value closer to observations ($Q_{ov} = 1.19$ PW). The larger overturning bias in CM2.1 is consistent with the larger warm bias in the zonal-mean temperature at depth (Fig. 3), coupled with the shallower return flow of NADW, which causes a weighting toward the warmer parts of the deep water.

These differences can also be assessed by decomposing the volume transport at 26.5°N in 1°C temperature bins to identify the temperature classes in which the models are biased compared with observations. The magnitude of the binned transports is generally larger in CM2.1 and CCSM4 than in RAPID (Fig. 7). The main differences appear for temperature classes above 24°C and below 10°C, the latter corresponding to the lower NADW, which is not well represented in the models, as mentioned earlier in this study. In RAPID the waters that are transported southward by the MOC have a temperature range quite equally distributed between 2° and 5°C, and the total southward transport for temperature classes under 10°C equals 17.5 Sv. In CM2.1 and CCSM4 the southward transport summed over the same temperature classes is stronger, reaching 19.9 Sv in CM2.1 and 18.7 Sv in CCSM4. It is also more concentrated in fewer bins because the NADW flow is too warm, missing the 2°C class entirely. The southward flow temperature, hence, reaches 8°C in CM2.1 and 7°C in CCSM4. Note that the lack of northward flow of AABW in Fig. 7a results from the choice of temperature classes that were used, where the coldest class in RAPID runs from 1.5° to 2.5°C, whereas the bottom water is all warmer than 1.5°C and hence cannot be distinguished from the coldest class of NADW. If the focus were on characterizing bottom water, using 0.5°C temperature classes would allow a better separation between NADW and AABW.

Finally, the differences between the models and observations can be assessed by breaking down the total overturning heat transport into an Ekman contribution...
and a geostrophic contribution, where the Ekman contribution is given by

$$Q_{ov}^E = -\int_0^L \frac{\rho}{f} \tau_x (T_{Ek} - \bar{T}) \, dx,$$

(3)

and the geostrophic contribution is the residual. Here $\tau_x$ is the zonal wind stress, $C_p$ is the specific heat capacity of seawater, $f$ is the Coriolis parameter, $T_{Ek}$ is the temperature of the Ekman layer, and $\bar{T}$ is the basin-average ocean temperature (Böning and Herrmann 1994). This assumes that the Ekman transport is balanced by a barotropic return flow at the depth-averaged temperature. While this has been shown to be valid for fluctuations in Ekman transport (Jayne and Marotzke 2001), it does not necessarily hold for the time-mean flow, and in this sense it is an arbitrary decomposition (Bryden et al. 1991). Nevertheless, it is a useful diagnostic as it allows the overturning heat transport to be separated into a part related to the ageostrophic surface Ekman transport and a part related to the baroclinic, zonally averaged geostrophic circulation. The breakdown of $Q_{ov}$ into these components is shown in Table 1 for both models and observations. Since it is not possible to easily determine the mean temperature of the Ekman layer in the models, and in order to be consistent with the RAPID calculations, $T_{Ek}$ is taken to be the sea surface temperature, which contributes only a small uncertainty to the Ekman heat transport (Johns et al. 2011). Both CM2.1 and CCSM4 overestimate the mean Ekman heat transport across 26.5°N compared with observations. In RAPID, the mean Ekman heat transport equals 0.27 PW and is associated with a northward mass transport of 3.5 Sv (Johns et al. 2011). Note that the Ekman transport in RAPID is about 0.25 Sv smaller than that derived from the climatological NCEP reanalysis because of a strong southward transport anomaly that occurred in March 2005 (Kanzow et al. 2010; Johns et al. 2011). In the models, the mean Ekman heat transport is 0.31 PW in CM2.1 and 0.32 PW in CCSM4, giving a relative contribution to the total $Q_{ov}$ of 29% and 27%, respectively, while it accounts for about 23% of the mean $Q_{ov}$ in RAPID. These discrepancies are mainly due to zonal wind stress biases with too-strong easterlies in the subtropics in both models, resulting in too-large northward Ekman transports at 26.5°N (5.2 Sv in CM2.1 and 4.5 Sv in CCSM4). This will be investigated in more detail in future work where the mechanisms of the seasonal variability of the MHT at 26.5°N will be assessed. The actual biases in the Ekman heat transport in the models are smaller than the corresponding biases in the Ekman transport because the mean temperature difference ($T_{Ek} - \bar{T}$) is smaller in the models than in the observations, with a mean value of 17.0°C in CM2.1 and 18.4°C in CCSM4 instead of 19.3°C in RAPID. This is due primarily to the warmer deep temperatures in the models, as noted previously, and also partly to lower sea surface temperatures in the models, especially in CM2.1 (Fig. 3). Despite this bias, in both models the geostrophic component provides the largest contribution to the mean MHT, consistent with observations. The geostrophic component is nevertheless biased low in both models, by about 15% in CM2.1 (0.77 PW) and 4% in CCSM4 (0.87 PW), compared to observations (0.91 PW). The heat

![Fig. 7](image-url)
transport carried by the basinwide baroclinic circulation is therefore too weak in the models. Part of this bias is related to the too-shallow and warmer NADW return flow in the models, but another part of it is caused by a too-weak near-surface northward flow of the geostrophic overturning cell, as can be seen from a careful examination of Figs. 3 and 6. In Fig. 3, the models and observational overturning streamfunction profiles all lie nearly on top of each other in the upper 500 m and reach almost exactly the same value at 400 m, even though the northward Ekman transport is 1.0–1.5 Sv larger in the models. This means that the very upper part of the geostrophic northward flow is too weak in the models. In Fig. 6b, this is also evidenced in the cumulative overturning heat transport, which is greater in RAPID over the top 500 m, even though it has a weaker Ekman transport. The low biases in the geostrophic overturning heat transport in the models are thus due to two factors, 1) a too-weak northward geostrophic transport in near surface layers where temperatures are warm and 2) a too-shallow deep NADW return flow—and, secondarily, an overall mean bias in deep temperatures (especially in CM2.1) resulting in a warm bias in the lower limb of the overturning cell. The approximately correct value of the total $Q_{ov}$ in CCSM4 therefore results from a compensation between a slightly too-weak geostrophic and slightly too-strong Ekman contribution, while in CM2.1 the bias can be attributed entirely to the geostrophic contribution, which is partially offset by the Ekman contribution.

b. The horizontal heat transport

We now assess the reasons for the bias in the gyre heat transport, as this is a common source of MHT underestimate in both models. The potential temperature and velocity anomalies with respect to the zonal mean are shown in Figs. 5 and 8, keeping in mind that their product is what makes up the horizontal component of the MHT. In Fig. 8 we focus on the velocity anomalies near the western boundary, which provide the largest contribution to the horizontal heat transport. Since no direct observations comparable to WOA are available for the time-mean velocity field, we show as a reference the mean circulation in the eddy-permitting Estimating the Circulation and Climate of the Ocean, phase II (ECCO2), estimate. The ECCO project aims to produce a best possible, global, time-evolving synthesis of most available ocean and sea ice data at a resolution that admits ocean eddies (Menemenlis et al. 2008). The ECCO2 estimate is obtained by least squares fit of a global, full-depth, eddy-permitting ocean and sea ice configuration of the Massachusetts Institute of Technology general circulation model (MITgcm) to the available satellite and in situ data. The data used here are from the model version based on a cubed-sphere grid with 18-km horizontal grid spacing (Menemenlis et al. 2005). The reader is referred to the ECCO2 homepage (http://www.ecco2.org) for more details and for links to the data. The mean velocity field shown in Fig. 8 was computed from monthly averages between April 2004 and October 2007 to be consistent with RAPID. We only use ECCO2 here to show a 3D estimate of the velocity field at 26.5°N to compare with the models: hence, whether the MHT–MOC relationship is well represented in that synthesis is out of scope of this analysis. Note that another eddy-permitting solution produced by the GFDL CM2.5 coupled model (Delworth et al. 2012) gives a very similar mean velocity at 26.5°N, and the improvement of the MHT–MOC relationship with resolution based on that model will be investigated in a future study.

In the eddy-permitting estimate, the velocity anomalies with respect to the zonal mean are characterized by strong northward anomalies at the western boundary in the upper 1000 m, split between the model representation of the Florida Current and Antilles Current and weaker southward anomalies below, associated with the deep western boundary current (DWBC). These
positive anomalies are weaker in CM2.1 and CCSM4 and extend over a larger area, which is largely due to the different resolutions of the topography. The corresponding temperature anomalies that contribute to $Q_{\text{gyre}}$ are shown in Fig. 9. The same anomalies were shown in Figs. 5d–f for the whole section, whereas we focus here on the western boundary. Given that the WOA climatology does not resolve the western boundary region well, we use the new RAPID hydrographic climatology described in Johns et al. (2011) that was produced using the HydroBase data analysis package (Curry 1996) combined with all available CTD and station data collected near the RAPID–MOCHA line. This climatology has a higher zonal resolution than WOA ($0.2^\circ$ versus 1$^\circ$) and therefore provides a better representation of the Florida and Antilles current regions. Indeed, as noted by Johns et al., the temperature anomalies in the Florida Current are warmer than the zonal mean only in the upper water column and cooler in the deeper part of the current, consistent with previous observations by Hall and Bryden (1982). This is the result of the strong uptilt of the thermocline toward the boundary across the Florida Current. A sharp zonal gradient is found at 500-m depth with cold anomalies very localized at the boundary and warm anomalies east of it. As a result, even though the velocity anomalies in the Florida Current are all strongly positive with respect to the zonal-mean flow, the net contribution of the Florida Current to the gyre heat transport in observations is almost negligible, owing to these contrasting temperature anomalies within the current. The cold anomalies are not well represented in WOA because of lack of resolution. Previous studies suggested that models tend to overestimate this cold core (Jia 2003). As shown in Figs. 9b and 9c, CM2.1 and CCSM4 reproduce the dipolar structure at the western boundary, with warm temperature anomalies overlying colder ones, but the
depth and extension of the anomalies are quite different from observations. The warm anomalies are located too close to the boundary and do not extend deep enough in the offshore region. This leads to a cold bias over most of the western boundary (Figs. 9d,e), strongly reducing or even reversing the oceanic heat transport by the gyre circulation. The discrepancy with the observations therefore appears to be mainly because of a lack of model resolution and corresponding impacts on the representation of the velocity and temperature structure in the western boundary layer.

This temperature bias appears as the dominant source of the horizontal heat transport discrepancy in both models. The cumulative vertical integral of the gyre heat transport is shown in Fig. 6c. The gyre component of the temperature transport is negatively biased in the two models, with errors appearing in the upper ocean, starting at about 300 m and reaching their maximum amplitude at about 800 m, then remaining constant as depth increases. As a result, the gyre heat transport simulated by CM2.1 and CCSM4 is lower than in RAPID and is even reversed, with a southward negative transport of −0.03 PW in CM2.1 and −0.01 PW in CCSM4, while RAPID shows a northward positive transport of +0.15 PW. Even when taking into account the MHT intrinsic variability and the uncertainty due to sampling of the outputs, the simulated mean gyre heat transport is never northward (appendix A). The source of the bias in the upper 800 m in the models is consistent with the cold temperature bias described in Fig. 9. Our results suggest that the underestimated heat transport is mainly the result of a biased gyre heat transport in CCSM4 with errors arising in the upper ocean, while it is due to errors in both overturning and gyre components in CM2.1.

c. Assessing the physical meaning of the slope in the MHT/MOC regression

To better understand what controls the sensitivity of the MHT to the MOC, we investigate the parameters that set the slope shown on Figs. 4c and 4d, which corresponds to the \( Q_{ov} \) regression on the MOC. We showed in Fig. 3 that both CM2.1 and CCSM4 overestimate the magnitude of the MOC maximum, which would tend to overestimate \( Q_{ov} \) compared with RAPID. However, \( Q_{ov} \) also depends on the zonal-mean potential temperature difference between the upper and lower parts of the NADW cell, and the bias in this temperature gradient partly compensates for the overestimation of \( Q_{ov} \) due to the MOC magnitude. Here \( Q_{ov} \) can be written as follows (Jia 2003; Marshall and Plumb 2008):

\[
Q_{ov} = \rho_0 C_p \Psi_{\max} \Delta T = \rho_0 C_p \Psi_{\max} (T_{\text{upper}} - T_{\text{lower}}),
\]

where \( \Psi_{\max} \) is the maximum magnitude of the MOC and \( T_{\text{upper}} \) and \( T_{\text{lower}} \) are the flow-weighted zonal-mean potential temperature in the upper and lower limbs of the overturning cell:

\[
T_{\text{upper}} = \int_{-H}^{z_{\max}} \nabla \psi dz \text{ and } T_{\text{lower}} = \int_{-H}^{z_{\max}} \nabla \psi dz,
\]

where \( \nabla \psi \) are the zonal-mean potential temperature and Eulerian velocity, \( H \) is the depth of the ocean, and \( z_{\max} \) refers to the depth of \( \Psi_{\max} \) which can be identified in Fig. 3. This yields \( \Delta T = 15.4^\circ \text{C} \) in RAPID, \( \Delta T = 15.1^\circ \text{C} \) in CCSM4, and \( \Delta T = 12.9^\circ \text{C} \) in CM2.1. The larger bias in CM2.1 is mainly the result of the too-cold upper ocean and too-warm lower ocean, as shown in Figs. 3 and 5 and discussed earlier.

If we consider the following decomposition:

\[
\Psi_{\max} = \langle \Psi_{\max} \rangle + \psi_{\max} \Delta T = \langle \Delta T \rangle + \Delta T',
\]

where angle brackets represent the time average and primes the departure from it, Eq. (4) yields

\[
Q'_{ov} = \rho_0 C_p (\langle \Delta T \rangle \Psi_{\max} + \Delta T' \langle \Psi_{\max} \rangle + \Delta T' \psi_{\max}).
\]

Each of these terms needs to be considered to fully characterize the slope between \( Q_{ov} \) and the MOC. If \( \Delta T \) were constant in time, then the first term on the rhs of Eq. (7) would control the regression slope, and one would expect an approximately correct slope in CCSM4 and an underestimate in CM2.1. However, as shown in appendix B, CCSM4 slightly underestimates the sensitivity of \( Q_{ov} \) to the MOC, and CM2.1 slightly overestimates it because of differences in the additional terms. The \( y \) intercept of this regression is also better represented in CCSM4 than in CM2.1. As shown in appendix B, the \( y \) intercept is mainly determined by the mean MOC magnitude and by the correlation between MOC and temperature variations, which are both better represented in CCSM4.

That the regression slope between \( Q_{ov} \) and \( \Psi_{\max} \) in CM2.1 is approximately correct, even though the mean \( \Delta T \) between the upper and lower limbs of the cell is too small, implies that the correlation between the time fluctuations in \( \Psi_{\max} \) and those of \( \Delta T \) is too large, as discussed in appendix B and shown in Table B1. To understand the reasons for this, we now focus on the respective roles of Ekman and baroclinic geostrophic transport variability in determining the sensitivity of the MHT to the MOC and, more specifically, in determining
the sensitivity of \( Q_{\text{ov}} \) to the MOC. As in section 4a, we consider the total \( Q_{\text{ov}} \) to be composed of two parts, an Ekman contribution (\( Q_{\text{Ek}}^{\text{ov}} \)) and a geostrophic contribution (\( Q_{\text{geo}}^{\text{ov}} \)). The sensitivity of the overturning heat transport to changes in the Ekman transport can be approximated, from Eq. (3), by

\[
dQ_{\text{Ek}}^{\text{ov}} / dV_{\text{Ek}} = \rho_0 C_p \Delta T_{\text{Ek}},
\]

where \( V_{\text{Ek}} \) is the Ekman transport and \( \Delta T_{\text{Ek}} = T_{\text{Ek}} - T \) is the difference between the Ekman layer temperature and the basin-averaged temperature. This assumes that fluctuations in Ekman transport are rapidly compensated in the ocean by a depth-independent transport, as demonstrated by Jayne and Marotzke (2001) and Kanzow et al. (2007). The anomaly in the overturning streamfunction associated with a change in Ekman transport thus consists of a sharp increase from the surface to the depth of the Ekman layer, equal to the value of the Ekman transport, with an underlying linear decrease to zero at the bottom associated with the depth-independent compensation (Fig. 10). If this Ekman streamfunction anomaly is then subtracted from the total overturning streamfunction anomaly at each time, the remaining fluctuations represent the variations in the geostrophic overturning. In both models and in the observations, we have performed this decomposition to isolate the Ekman and geostrophic changes of the overturning circulation, similar to that done in Johns et al. (2011). The Ekman heat transport at each time is calculated from Eq. (3), and the remaining geostrophic contribution \( Q_{\text{geo}}^{\text{ov}} \) is obtained by differencing this with the total \( Q_{\text{ov}} \). Defining the maximum of the geostrophic streamfunction as \( \Psi_{\text{geo}}^{\max} \), the sensitivity of the geostrophic overturning heat transport to changes in the geostrophic streamfunction can then be determined by a linear regression of \( Q_{\text{geo}}^{\text{ov}} \) onto \( \Psi_{\text{geo}}^{\max} \). This sensitivity will depend on the depth of \( \Psi_{\text{geo}}^{\max} \) as well as the typical shape of the \( \Psi_{\text{geo}}(z) \) fluctuations since this will determine the average temperatures of the upper and lower branches of the compensating geostrophic circulation. The different shape of the geostrophic profiles between the models and the observations in Fig. 10 suggests an amplification of baroclinic variability at depth in CM2.1 and CCSM4 that is not found in RAPID. Although the physical processes explaining this difference remain to be determined, the decomposition of the geostrophic overturning fluctuations into EOF modes suggests that this feature at depth results from second and higher modes of variability in the models that account for a larger fraction of the total variance than in observations (not shown).

The computed values for \( \Delta T_{\text{geo}} \) for RAPID, CM2.1, and CCSM4 are 15.1°C, 14.6°C, and 13.4°C, respectively. The corresponding values for the models are 19.3°C, 17.0°C, and 18.4°C. Thus, in each case, variations in \( Q_{\text{ov}} \) have a higher sensitivity to Ekman transport fluctuations than geostrophic overturning fluctuations because \( \Delta T_{\text{Ek}} > \Delta T_{\text{geo}} \). On the other hand, for both the Ekman and geostrophic fluctuations the sensitivities (\( \Delta T_s \)) are lower in both models than in the observations. This means that, if the models were to have the same proportions of Ekman and geostrophic

![Fig. 10. Profile of the MOC standard deviation and the contribution of Ekman and geostrophic fluctuations to the total MOC variability in (a) RAPID, (b) CM2.1, and (c) CCSM4. The methodology is detailed in the main text.](image-url)
contributions to the overturning variability as in the observations, the overall sensitivity of $Q_{ov}$ to MOC fluctuations would be underestimated. However, as shown in Fig. 10, the respective contribution of Ekman and geostrophic fluctuations to the total overturning variability differs between models and observations and between the two models as well. In RAPID the geostrophic variability has higher amplitude than the Ekman transport variability, while in CM2.1 the Ekman contribution is dominant and in CCSM4 the two have nearly equal amplitude. Both of the models underestimate the geostrophic fluctuations by a factor of $\sim 2$, and both have weaker Ekman transport variability than in RAPID, more so in CCSM4. The fact that both models show a larger relative contribution of Ekman transport fluctuations to the MOC variability, compared to observations, means that the overall sensitivity of $Q_{ov}$ to MOC fluctuations will be more strongly weighted toward the Ekman sensitivity than the geostrophic sensitivity (i.e., the $\Delta T_{Ek}$ versus the $\Delta T_{geo}$). It is for this reason that the regression slopes between $Q_{ov}$ and $\Psi_{max}$ are approximately correct in the models, even though their Ekman and geostrophic sensitivities are both independently too low. It is interesting to note that the higher proportion of Ekman to geostrophic variability in CM2.1 is accompanied by a larger bias in $\Delta T_{Ek}$ ($17.0^\circ$ versus $19.3^\circ$C), compared to that in CCSM4 ($18.4^\circ$ versus $19.3^\circ$C), so the overall impact on the $Q_{ov}$ sensitivity is comparable between the two models.

One can reach the same conclusion by simply comparing the relative magnitudes of $Q_{ov}^{Ek}$ and $Q_{ov}^{geo}$ fluctuations in the models with that of the observations (Table 2). The standard deviation of $Q_{ov}^{Ek}$ is nearly the same as that of $Q_{ov}^{geo}$ in the observations, but it is nearly two times larger in CM2.1 and about 1.6 times larger in CCSM4. Hence, both models underestimate the relative contribution of baroclinic geostrophic variability in controlling the fluctuations of $Q_{ov}$.

5. Conclusions and discussion

The RAPID–MOCHA observations of the Atlantic MOC and associated meridional heat transport were used in this study to determine the fidelity of the simulated total MHT in two CMIP5 climate models, GFDL CM2.1 and NCAR CCSM4. We showed that both CM2.1 and CCSM4 underestimate the total mean meridional heat transport by more than 10% at 26.5°N, despite a slightly stronger-than-observed MOC magnitude. We decomposed the MHT into its overturning and gyre contributions and showed that the main reason for the too-small MHT is a biased gyre heat transport in both models, added to a too-small overturning heat transport in CM2.1. The low bias in the overturning heat transport in CM2.1 was found to be primarily due to an understimation of the temperature difference between the upper and lower NADW cell in CM2.1, which creates an error that is partly compensated by a too-large MOC maximum. This bias is much smaller in CCSM4, partly because the model includes a parameterization of Nordic Seas overflows leading to a more realistic representation of the NADW cell. We analyzed the relative importance of Ekman and geostrophic components and showed that the overturning heat transport in both models has a relatively too-large component related to the Ekman circulation and a too-weak component carried by the basinwide baroclinic circulation. Our results stress that, in the two coupled models analyzed, the MOC is the dominant contributor to the Atlantic mean MHT and its misrepresentation does affect the MHT simulation; however, the biased gyre heat transport, even with its much smaller contribution to the total mean MHT, is an important source of error. In RAPID, the large-scale gyre circulation contributes to about 10% of the total northward MHT at 26.5°N, but the corresponding transport in CM2.1 and CCSM4 is southward, thus decreasing the total MHT. Our analysis suggests that this bias arises mainly from a misrepresentation of potential temperature and velocity fields at the western boundary in the Straits of Florida, which is not well represented at this resolution. Both models indicate a cold bias collocated with northward velocity anomalies with respect to the zonal mean at the western boundary, yielding an anomalous southward heat transport by the gyre circulation.

The sensitivity of MHT variability to MOC variability in both models and observations was further assessed by comparing the regression slopes between MHT and MOC. A linear relationship was found between MHT and MOC in both models, with quite good agreement with RAPID. We showed that both models accurately simulate the observed dominant contribution of the overturning in the MHT–MOC relationship with a correct sensitivity in CM2.1 and a slightly too-small one in CCSM4. A detailed assessment of these sensitivities showed that correlations between MOC fluctuations and temperature anomalies were important in setting the

<table>
<thead>
<tr>
<th>Model</th>
<th>Std dev $Q_{ov}^{Ek}$ (PW)</th>
<th>Std dev $Q_{ov}^{geo}$ (PW)</th>
<th>Std dev $Q_{ov}$ (PW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RAPID</td>
<td>0.37</td>
<td>0.29</td>
<td>0.26</td>
</tr>
<tr>
<td>CM2.1</td>
<td>0.21</td>
<td>0.17</td>
<td>0.09</td>
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<tr>
<td>CCSM4</td>
<td>0.17</td>
<td>0.13</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Table 2. Standard deviation of $Q_{ov}$, $Q_{ov}^{Ek}$, and $Q_{ov}^{geo}$ in RAPID, CM2.1, and CCSM4. The standard deviations for RAPID are computed using 30-day low-pass filtered data.
overall sensitivity of the MHT to MOC changes and that considering only the time-mean temperature difference of the upper and lower branches of the overturning circulation leads to an underestimate of the sensitivity. We also found that the sensitivity of the gyre heat transport to the MOC was poorly simulated in both models yielding errors in the sensitivity of the total MHT. In observations, the slope between \( Q_{\text{gyre}} \) and the MOC is small but positive, contributing to increase the MHT sensitivity, whereas it was found to be slightly negative in CM2.1 and CCSM4, thus decreasing the sensitivity of the total MHT to the MOC.

The gyre circulation variability appears therefore as a source of bias, not only for simulating the mean MHT but also in affecting its variability and sensitivity to MOC fluctuations. Most of the gyre variability is wind driven; therefore, biases in the model atmospheric winds will contribute to gyre circulation errors and associated errors in the zonal temperature distribution. Additional hindcast experiments have been performed with the oceanic component of CCSM4 forced by observed atmospheric fluxes. Repeating the regression analysis between MHT and MOC in these ocean-only simulations yields a slope comparable to observations with, in particular, the correct gyre transport sensitivity (not shown). This suggests that atmospheric fluxes are an important source of errors in simulating the MHT–MOC relationship. The horizontal circulation variability is also closely related to the Florida Current, which is not well represented in the coupled models, partly because of an overly coarse resolution. Significant improvements in the mean potential temperature and velocity are found when oceanic resolution is increased, like in the ECCO2 solution shown in this paper, suggesting that a better representation of the oceanic thermocline and better resolved boundary currents could significantly improve the representation of the MHT. While oceanic eddies can clearly affect the climatological state and variability at the western boundary, and thereby the MHT, indirectly, analysis of RAPID data revealed a small eddy contribution to the total MHT at 26.5°N (Johns et al. 2011). The direct contributions from subgrid-scale parameterizations have been estimated to be small in the models too and were therefore not included in this study. The sensitivity of the MHT to model resolution will be addressed in future work, using the GFDL eddy-permitting and eddy-resolving latest coupled models (Delworth et al. 2012).

Although both models show a strong relationship between MOC and MHT and correctly reproduce the observed sensitivity of the overturning heat transport to the MOC, the high correlation was mainly attributed to a too-strong sensitivity to Ekman variability in both models, compensating a too-weak sensitivity to baroclinic geostrophic variability, particularly in CM2.1. The dominant contribution of simulated Ekman variability is in agreement with previous modeling studies (Böning et al. 2001; Jayne and Marotzke 2001; Sarojini et al. 2011) but does not agree with observational analyses that show geostrophic fluctuations account for about half of MHT variability and more than half of MOC variability (Kanzow et al. 2010; Johns et al. 2011). Recent work by Sarojini et al. (2011) showed that other non-Ekman ageostrophic terms that have been neglected in observational estimates are small and are thus not likely to be the cause of disagreement between models and observations. We can partly attribute these differences to wind biases in the tropical North Atlantic (Doi et al. 2012) that lead to an overestimation of Ekman mean heat transport in CM2.1 and CCSM4, as in other coupled models (Sarojini et al. 2011). Further, the weaker variability in geostrophic overturning in the models compared to observations favors an overestimation of MHT sensitivity to Ekman transport. However, the mechanisms explaining the more prominent role of geostrophy in the observations are still not fully understood and require further investigation.

In this paper, we only used the first 3.5 years of RAPID data to be consistent with previous publications. The main results of this study do hold when using the longer updated 7-yr record (not shown). The direct observations of MOC and MHT provided by the RAPID array proved to be very valuable to evaluate the models MHT at 26.5°N and identify the biases that were the source of the too-weak MHT. Although our study focused on only two climate models, the underestimation of the Atlantic MHT is a bias common to many coupled models at this resolution (Jia 2003; Pachauri and Reisinger 2007). The discrepancies relative to observations that were identified in CM2.1 and CCSM4 might therefore exist in a larger set of the CMIP5 models. The mechanisms of variability of the MOC are, however, largely model dependent, and the effect this might have on the MHT needs to be investigated in detail in more than these two models, including higher-resolution coupled models.

Finally, we have characterized the link between MOC and MHT at the latitude of the RAPID–MOCHA line around 26.5°N, which is located near the latitude of the maximum observed oceanic heat transport. While our choice was motivated by the presence of continuous monitoring of the MOC and MHT, the results presented here cannot be generalized to the whole Atlantic basin. One expects the dominant role of the overturning heat transport to decrease toward higher latitudes, with the gyre component having a larger contribution...
in the subpolar region where zonal gradients of temperature are larger. This stresses that additional observations of the MOC in the subpolar gyre would be needed to realistically assess the variability of the MOC and associated MHT across the whole Atlantic basin.

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APPENDIX A

Uncertainty Associated with Models and Observations Sampling

The link between MOC variability and that of the MHT at 26.5°N has been assessed by regressing the MHT on the MOC and comparing the model regression coefficients to those obtained using observations (Fig. 4). Monthly mean outputs from 50-yr-long segments have been used for the models, whereas the observational analysis was based on 10-day averages covering 3.5 yr. We argued in the main paper that the use of 50 yr for the models versus 3.5 yr in RAPID does not affect our main conclusions because the simulated relationship between MOC and MHT is robust and does not depend on model or data sampling. We address this issue in more details here by plotting the regression coefficient of the MHT on the MOC for different simulation lengths varying from 3.5 to 50 yr (Fig. A1). We estimate the uncertainty of the slope by showing as an error bar the standard deviation of the regression coefficient over the corresponding segment. The results are shown in Fig. A1 for the total MHT, the overturning MHT ($Q_{ov}$), and the gyre MHT ($Q_{gyre}$). For the total MHT, the mean slope simulated by CM2.1 is larger than observed when computed over 3.5 yr and it decreases toward a slightly lower value than in RAPID as the length of the simulation increases. The mean value in CCSM4 is always smaller than observed, whatever the length of the simulation. The mean regression coefficient for $Q_{ov}$ slightly decreases as the length of the simulation increases in CM2.1, but it remains above the observed value. The mean slope is much more constant in CCSM4, always slightly below observations. The slope attributed to the gyre contribution is close to zero for the shortest simulations in CM2.1 and becomes more negative as the length of the time series increases, whereas in CCSM4 it is always negative. Note that the two models converge toward the same value, biased negatively compared with observations, for a 50-yr-long simulation (Fig. A1c). The variability is larger in CM2.1 than in CCSM4 for simulations longer than 15 years, yielding larger error bars. However, this is not a very accurate measure of uncertainty given that the longer the segment, the fewer the number of segments that can be defined (e.g., only two 25-yr segments can be defined over a 50-yr-long simulation; hence, the error bar indicates the distance between those two values). Overall, the mean value of the regression coefficient does not change much as the length of the simulation varies and, even when the largest possible values are considered for the models, the conclusions about the MHT–MOC relationship remain unchanged. This illustrates that the results do not depend on the length of the simulations and that the main features highlighted in our study are robust with sampling: the contribution of the overturning variability to the MHT–MOC relationship tends to be slightly too large in CM2.1, slightly too small in CCSM4, and the contribution of the gyre variability is negatively biased in both models. Comparable results are found for the present-day and historical simulations (not shown).

The RAPID data used in this study are derived from twice-daily data further sampled as 10-day averages. Given that we use monthly mean outputs for the model analyses, the question of the different sampling arises. Fig. A2 shows the scatterplots of the MHT/MOC regressions in RAPID for the 10-day averages used in the main paper and for 30-day averages to compare with the sampling of models outputs. Although the number of points is reduced for longer averages, increasing the spread of the data, the regression coefficients indicate relatively little variation (Fig A2). The MHT–MOC relationship in RAPID described in Fig. 4 is therefore robust, and the main results of this study do not depend on the temporal sampling of the model and data outputs.
What Sets the Slope and y Intercept of the MHT Regression on the MOC?

The overturning heat transport can be defined by the exact relationship

\[ Q_{ov} = \rho_0 C_p \Psi_{\text{max}} \Delta T, \]

which can be written when time fluctuations are accounted for:

\[ Q_{ov} = \rho_0 C_p (\langle \Delta T \rangle \langle \Psi_{\text{max}} \rangle + \langle \Delta T \rangle \Psi_{\text{max}}' + \Delta T' \langle \Psi_{\text{max}} \rangle \), \tag{B1} \]

using the same notation as in the main manuscript. The linear regression of \( Q_{ov} \) onto \( \Psi_{\text{max}} \) is performed by fitting the line \( \hat{y}_i = ax_i + c \) to the exact relation \( y_i = A_i x_i \) and minimizing the squared residual \( \sum e_i \), where \( e_i = y_i - \hat{y}_i \) (Wilks 2006). We have \( y_i = Q_{ov,i} = \rho_0 C_p \Delta T_{\text{ov},i} \), with \( x_i = \Psi_{\text{max},i} \). Hereafter, \( \rho_0 C_p \) and the subscripts of \( \Psi_{\text{max}} \) and \( \Delta T \) are dropped for better clarity. The slope of the regression is then given by

\[ a = \frac{\sum (x_i - \langle x \rangle)(y_i - \langle y \rangle)}{\sum (x_i - \langle x \rangle)^2}, \tag{B2} \]

where \( \langle x \rangle = \langle \Psi \rangle \) and \( \langle y \rangle = \langle \Psi \rangle \langle \Delta T \rangle + \langle \Psi' \Delta T' \rangle \). Equation (B2) can be then written as

\[ a = \frac{\sum \Psi_i' \langle \Delta T \rangle + \langle \Psi \rangle \Delta T' + \Psi_i' \Delta T' - \langle \Psi' \Delta T' \rangle}{\sum \Psi_i'^2}, \tag{B3} \]
which can be simplified to

\[ a = \langle \Delta T \rangle + \langle \Psi \rangle \frac{\sum \Psi_i' \Delta T_i'}{\sum \Psi_i^2} + \frac{\sum \Psi_i^2 \Delta T_i'}{\sum \Psi_i'^2} - \langle \Psi' \Delta T' \rangle \frac{\sum \Psi_i'}{\sum \Psi_i'^2}. \]

(B4)

where the last term on the rhs is identically equal to zero. We evaluate and show in Table B1 the contributions of the first three terms on the rhs of Eq. (B4), denoted by \( a_1, a_2, \) and \( a_3 \), respectively. We can interpret these different terms as follows: \( a_1 \) represents the effect of current anomalies advecting the mean temperature, \( a_2 \) represents the mean currents advecting thermal anomalies that project onto current anomalies, and \( a_3 \) is the nonlinear advection that projects onto current anomalies. The slope is mainly determined by \( a_1 \) and \( a_2 \) in the models and in observations. If time variations of the zonal-mean temperature gradient were negligible, we would have \( \Delta T_i' = 0 \), and the slope would simply be determined by \( a_1 = \langle \Delta T \rangle \). However, as shown in Table B1, this approximation is not correct since using only the \( a_1 \) term would yield a slope that is smaller than observed in CM2.1, whereas it is comparable to observations, even slightly larger (Fig. 4c). The term \( a_2 \), which represents the correlation between the time fluctuations of \( C_{\text{max}} \) and those of \( \Delta T \), cannot be neglected. We find that CM2.1 simulates the correct slope because of a compensation between \( a_1 \), which is too small, and \( a_2 \), which is too large. CCSM4 gets the right \( a_1 \) and only slightly underestimates \( a_2 \) compared with RAPID, suggesting that it gets the right slope for the right reasons. This decomposition explains the differences of slope between the two coupled models and observations, which cannot be explained using only \( \langle \Delta T \rangle \). The reason for the differences between the two models in the \( a_2 \) term has not been clearly identified. It could result from thermal anomalies being too large or projecting too much on current anomalies, which could result from a circulation that is too shallow and Ekman dominated, with too little contribution of the baroclinic geostrophic transport, as suggested by Fig. 10 and discussed in section 4c. It could also be linked to the two models’ different parameterizations, grid structure, or tuning processes. Additional sensitivity experiments would be needed to fully understand this source of difference.

We can also identify what sets the \( y \) intercept in the regression of \( Q_{\text{ov}} \) on the MOC and determine why CM2.1 and CCSM4 have \( y \) intercepts different from RAPID, resulting in a smaller \( Q_{\text{ov}} \) in the case of CM2.1. The \( y \) intercept is defined by

\[ c = \langle y_i - ax_i \rangle, \]

(B5)

### Table B1: Slope contributions and \( y \) intercept contributions in the regression of \( Q_{\text{ov}} \) on \( \Psi_{\text{max}} \).  

<table>
<thead>
<tr>
<th>Model</th>
<th>( A ) (PW Sv(^{-1}))</th>
<th>( a_1 = \langle \Delta T \rangle ) (PW Sv(^{-1}))</th>
<th>( a_2 = \langle \Psi \rangle \frac{\sum \Psi_i' \Delta T_i'}{\sum \Psi_i^2} ) (PW Sv(^{-1}))</th>
<th>( a_3 = \frac{\sum \Psi_i^2 \Delta T_i'}{\sum \Psi_i'^2} ) (PW Sv(^{-1}))</th>
<th>( \langle \Psi' \Delta T' \rangle ) (PW)</th>
<th>( -a_2 \langle \Psi' \Delta T' \rangle ) (PW)</th>
<th>( -a_3 \langle \Psi' \Delta T' \rangle ) (PW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RAPID</td>
<td>0.075</td>
<td>0.063</td>
<td>0.015</td>
<td>-0.002</td>
<td>-0.208</td>
<td>0.019</td>
<td>-0.272</td>
</tr>
<tr>
<td>CM2.1</td>
<td>0.078</td>
<td>0.053</td>
<td>0.027</td>
<td>-0.002</td>
<td>-0.515</td>
<td>0.008</td>
<td>-0.560</td>
</tr>
<tr>
<td>CCSM4</td>
<td>0.072</td>
<td>0.062</td>
<td>0.011</td>
<td>-0.001</td>
<td>-0.202</td>
<td>0.003</td>
<td>-0.216</td>
</tr>
</tbody>
</table>
where \( a \) is the regression slope. Using the above decomposition gives

\[
\langle y - ax \rangle = \langle \Psi \Delta \mathcal{T} \rangle - a_2 \langle \Psi \rangle - a_3 \langle \Psi \rangle. \tag{B6}
\]

The second and third terms, \(-a_2 \langle \Psi \rangle\) and \(-a_3 \langle \Psi \rangle\), are the dominant terms that determine the \( y \) intercept in the models and in observations, as indicated in Table B1. CM2.1 has a too-negative value for \(-a_2 \langle \Psi \rangle\) consistent with the shift in the slope in Fig. 4c, whereas CCSM4 gets about the right value. The bias in CM2.1 is due to both a too-large \( a_2 \), as highlighted in the slope description above, and a too-strong MOC magnitude leading to a too-large \( \langle \Psi \rangle \). These two factors are better simulated in CCSM4, leading to a \( y \) intercept comparable to RAPID.

REFERENCES


