Spatio-temporal patterns of Chaos in the Atlantic Overturning Circulation

Q. Jamet[1*], W. K. Dewar[1], N. Wienders[1] and B. Deremble[2]

[1]Department of Earth, Ocean and Atmospheric Science, the Florida State University, Tallahassee, Florida

[2]Laboratoire de Météorologie Dynamique, Paris, France

Key Points:

- We highlight the existence of a basin scale intrinsic mode of AMOC variability sharing similarities with the atmospherically forced mode
- The RAPID-MOCHA-WBTS array is found to be part of this basin scale mode; 50% of its interannual variability is ascribed as intrinsic
- Our results provide an estimation of the quantitative accuracy of the overturning variability within eddy-resolving ocean models

*The Florida State University, 117 N Woodward Avenue, Tallahassee, FL 32306-4320.

Corresponding author: Quentin Jamet, `qjamet@fsu.edu`

Abstract

Examining an ensemble of high-resolution (1/12°) North Atlantic ocean simulations, we provide new insights into the partitioning of the Atlantic Meridional Overturning Circulation (AMOC) variability between forced and intrinsic at low-frequency (2-30 years). We highlight the existence of a basin scale intrinsic mode that shares similarities with the atmospherically forced signal. The RAPID-MOCHA-WBTS array is found to be part of this mode, such that we ascribe 50% (∼0.8 Sv) of its interannual variability as intrinsic. At decadal time scales, intrinsic variability is rather small (∼0.2 Sv) compared to the recently observed 2-3 Sv AMOC downturn. This downturn is thus unlikely to be induced by locally generated intrinsic ocean dynamics. We interpret this intrinsic variability as 'chaotic', i.e. somewhat unpredictable, providing an estimation of the quantitative accuracy of AMOC variability within eddy-resolving numerical models.

1 Introduction

The Atlantic Meridional Overturning Circulation (AMOC) is an important oceanic component of the climate system, placing a premium on understanding its variability. It affects regional and global climate by modulating oceanic surface temperatures in the North Atlantic (Caesar et al., 2018; Knight et al., 2005; McCarthy et al., 2015), impacting precipitation over Europe (Sutton et al., 2012) and North Africa (Zhang et al., 2006) and influencing hurricane activity in North America (Goldenberg et al., 2001). The mechanisms driving AMOC variability remain however debated mostly due to the large spread in the simulated spatio-temporal patterns between models (Buckley et al., 2016), and due to the difficulties in validating numerical results against sparse and too short observational time series.

The atmosphere is thought to drive a significant portion of AMOC variability at various time scales, such that increasing greenhouse gases are expected to induce a decline of the AMOC (Caesar et al., 2018; Kirtman et al., 2013; Saba et al., 2016). Recent observations suggest that this decline is underway (Smeed et al., 2018). The link between the observed decline and the simulated response to increased greenhouse gases remains unclear however, with observed patterns of surface ocean metrics associated with the observed AMOC decline that resemble those found in climate models (Smeed et al., 2018), but with a much larger amplitude than the simulated long-term forced trend (Smeed et al., 2014). Aside from surface forcing, the ocean also develops its own intrinsic variability (Penduff et al., 2011; Sérazin et al., 2015), so the AMOC strength does not only depend on the atmosphere. The contribution of such intrinsically driven ocean dynamics for the low-frequency AMOC variability has been recently underscored (Grégorio et al., 2015; Leroux et al., 2018), but our understanding of such processes is rather limited. This study sheds more light on such a contribution, and discuss implications for the interpretation of observational data set such as the RAPID-MOCHA-WBTS program.

To describe this variability, we use here an ensemble of numerical simulations of the North Atlantic. As we shall see, we taylored this ensemble to separate the AMOC variability into two contributions: The intrinsic (locally generated) variability and the atmospherically forced variability. We use a high resolution (1/12°), regional (20°S to 55°N) North Atlantic configuration to produce a 12-member ensemble consisting of 50-year long members, spanning the period 1963-2012. Each ensemble member corresponds to the same model configuration (external forcing and open boundary conditions). The only difference between the members of the ensemble is the initial condition. We provide a full description of the model in Section 2. In Section 3, we quantify the contribution of the internal ocean dynamics for the total low-frequency AMOC variability, and highlight the existence of a basin scale mode of intrinsic low-frequency AMOC variability. We propose a link between these results and observations at 26.5°N provided by the RAPID-MOCHA-WBTS program (McCarthy et al., 2015) in Section 4. We conclude and discuss the results in Section 5.

2 Model and Methods

The 12-members ensemble simulation is performed with a regional configuration of the Massachusetts Institute of Technology General Circulation Model (MITgcm, Marshall et al., 1997). The North Atlantic domain extends from 20°S to 55°N. The horizontal resolution is 1/12° and we have 46 layers on the vertical ranging from 6 m at the surface to 250 m at depth. Water masses that enter or leave the domain through the northern and the southern boundaries of the domain, as well as at the Strait of Gibraltar, are represented through the use of open boundary conditions derived from the 55-year long 1/12° horizontal resolution ocean-only global configuration ORCA12.L46-MJM88 (Molines et al., 2014; Sérazin et al., 2015), spatially interpolated on our model grid. At the surface, the ocean model is coupled to an atmospheric boundary layer model (Cheap-AML, Deremble et al., 2013). This approach is used to better represent air-sea exchanges, and to avoid the suppression of surface ocean dynamics caused by a prescribed atmosphere with an infinite heat capacity. The configuration is integrated forward in time for 50 years over the period 1963-2012 with a 12-members ensemble strategy. Further details on the configuration, the initial conditions, and the simulated North Atlantic oceanic mean state are given in Supporting Information.

To assess low-frequency intrinsic AMOC variability, we first remove trends and frequencies lower than 50 years in each ensemble member, estimated with a nonparametric locally estimated scatterplot smoothing (LOESS, Cleveland et al., 1988) operator. We compute a climatological annual cycle from the 50-year ensemble mean, and then remove this annual cycle from each member. Finally, the residuals are low-pass filtered with a 1-year cut-off period to remove the overwhelmingly large, daily to weekly variability due to atmospheric forcing. This filtering procedure isolates the ocean variability in the 2 to 30 year time bands (cf. Supporting Information).

We use a statistical approach to separate the intrinsically generated from the externally forced variabilities in our ensemble. We first compute an ensemble mean (50 years long time series) by averaging the oceanic state simulated by the 12 members. This time series represents the signal that is common to all members, and is assumed to originate from the external forcing, either from the surface or through the open boundaries. We interpret the ensemble mean as the forced signal, and define its temporal variance σ_F^2 following Leroux et al. (2018):

$$\sigma_F^2 = \frac{1}{T-1} \sum_{t=1}^{T} \left[\langle f_i(t) \rangle - \overline{\langle f_i(t) \rangle} \right]^2, \tag{1}$$

with T the length of the 50-year long simulations, $< . >$ the ensemble mean operator and $\overline{x}$ the time mean operator. Since only initial conditions differ between each realization, the residual of each member with respect to the ensemble mean is, by construction, due to ocean dynamics sensitive to the initial conditions. We interpreted this residual signal as the intrinsic variability, and define its variance σ_I^2 following Leroux et al. (2018):

$$\sigma_I^2 = \overline{\frac{1}{N-1} \sum_{i=1}^{N} [f_i(t) - \langle f_i(t) \rangle]^2}, \tag{2}$$

with $N = 12$ the number of members, $i = 1, .., N$ the member number. The total variance is simply defined as the sum of the intrinsic and the forced variance $\sigma_T^2 = \sigma_I^2 + \sigma_F^2$.

3 The intrinsic AMOC variability

We plot in Fig. 1 the intrinsic-to-total AMOC variance ratio $R = \frac{\sigma_I^2}{\sigma_T^2}$ in latitude-depth space. This provides a measure of the relative contribution of ocean internal dynamics for the total AMOC variance at interannual-to-decadal time scales. Intrinsic AMOC variability is routinely 50%, and exceeds 60% in the deep North Atlantic. Surface ratios are typically smaller, reflecting an increasing control of the AMOC by the atmosphere, although ratios of 30% are common. R exceeds 50% at 400 meters near 38°N where the Gulf Stream separates from the east coast of the United States, highlighting the strong meso-scale contribution to AMOC variability. Our estimates of the intrinsic-to-total ratio are somewhat larger than earlier studies for this region, but those were conducted with either a different method (Grégorio et al., 2015), or at coarser resolution (Leroux et al., 2018). At 26.5°N, R exceeds 40% as shallow as 500 meters, and increases near the bottom. Intrinsically driven versus forced AMOC variability at that location is further discussed in Section 4.

We now wish to extract the leading modes of forced and intrinsic AMOC variability in the latitude-depth space and compare their respective spatio-temporal patterns. We plot the first Empirical Orthogonal Function (EOF) of the ensemble mean AMOC on the top left panel of Fig. 2. It explains roughly 40% of the total forced AMOC variance, and is characterized by a broad positive signal from about 10°S to roughly 45°N, and negative signal elsewhere. The change of sign around 45°N is associated with a change of sign in the first EOF of the zonal winds (not shown). This pattern strongly resembles the delayed response of the AMOC to the North Atlantic Oscillation (NAO) usually identified in climate and ocean models (Deshayes et al., 2008; Eden et al., 2001; Gastineau et al., 2012). Furthermore, its associated Principal Component (PC, bottom left panel) peaks in the 2-3 and 6-8 year frequency bands typical of the NAO spectrum (Czaja et al., 2001; Reintges et al., 2017). We thus interpret this first EOF as the signature of a local, atmospherically forced AMOC variability.

To extract the leading mode of intrinsic AMOC variability, we perform a Principal Component Analyses for each ensemble residual and average the results (Fig. 2). We first note that the 10 first EOFs explain about 75% of the total intrinsic AMOC variance, while this number reaches more than 90% in the case of the forced signal. Such difference is indicative of a less organized intrinsic variability. The variance explained by the first intrinsic EOF is relatively high ($\sim$30%), and the averaging procedure highlights the emergence of a large scale mode of variability extending from 10°S to about 35°N with a maximum of about 1 Sv (1Sv = 10^6 m^3s^{-1}) around 20°N and 2000 m depth. This pattern exhibits spatial similarities with the atmospherically forced mode discussed earlier. Notable differences arise however in their spectral properties, where both intrinsic and forced leading modes peak (locally) at interannual time scales. The intrinsic PSD decreases monotonically at lower frequencies whereas the forced mode dominates at long time scales. This suggest that in the future generation of climate models with eddy resolving ocean models, projections of future changes in the North Atlantic overturning would be somewhat limited at interannual timescales, but might benefit of better predictive skills at decadal and longer timescales.

Finally, note that, although intrinsic variability controls more than 50% of the total variability in the Gulf Stream (Fig. 1), this region does not appear to be part of the leading mode of intrinsic AMOC variability. We suspect this is due to the mesoscale dynamics of this region, and Gulf Stream instabilities. As a result, although some signal are found in the second (Fig. S7) and subsequent EOFs for each individual member, they take place at slightly different locations such that averaging strongly damp their signature (Fig. 2, middle right panel). In other word, such modes of variability are member-dependent, and not considered here.

4 A focus on RAPID observations

We now wish to replace our ensemble-based results in the context of observations and discuss implications for the interpretation of observational data set. The RAPID-MOCHA-WBTS program (McCarthy et al., 2015) refers to a large, multi-national effort to monitor the strength of the AMOC, principally at 26.5°N in the North Atlantic. We have computed numerical equivalents of the observed AMOC by integrating net model northward transport across the North Atlantic, from Florida to the east coast of Africa (cf Supporting Information). Left panel of Fig. 3 compares the time evolution of the AMOC northward transport anomalies at 1200 meters, the maximum AMOC (Fig. 1), as measured by the RAPID array (red line) against that simulated by our 12 ensemble members (thin gray lines). We first note that our simulated AMOCs tend to underestimate the observations at the beginning of the record and overestimate them toward the end. This mismatch is associated with the observed weakening (2-3 Sv) AMOC trend from

2004 to 2012, a decrease argued to be due to a change in mid-ocean geostrophic (Smeed et al., 2014). Our simulations do not capture this over the 2005-2011 timeframe, and we do not either obtain intrinsic low-frequency variability this large. The PSD of the second intrinsic mode of variability is found to dominate over the forced component at decadal time scale (Fig. 2, bottom right panel). However, this second EOF explains only 10% of the intrinsic variance, such that it is likely to contribute only for $\sim$0.2 Sv to the total AMOC variability. We thus conclude that the observed 2-3 Sv AMOC transport downturn between 2004 and 2012 cannot be explained as local intrinsic variability only. We have conducted additional sensitivity experiments on the choice of open boundary conditions (not shown), and found that decadal AMOC variability at 26.5°N are mostly driven by remote signals. Further investigations of such remote signals in our North Atlantic regional configuration are underway and will be reported somewhere else.

The level of agreement between the observed and ensemble mean AMOC transports (Fig. 3, black line) remains however fairly high (correlation $r = 0.8$), with predominant near-seasonal fluctuations of $\sim$O(1 Sv). The pronounced weakening ($\sim$3 Sv) of the AMOC over the period 2009/2010 interpreted by others as due to atmospheric forcing (Roberts et al., 2013) is for instance well reproduced by all members. Each exhibits peculiarities however, such that AMOC variability is also member-dependent, highlighting the presence of an intrinsic variability at that location. At 26.5°N, our estimate of the intrinsic-to-total variance ratio R exceeds 40% at 1200 meters, the maximum AMOC (Fig. 1). The power spectral analysis of the simulated time series (Fig. 3, right panel) reveals that intrinsic ocean dynamics contributes about 50% at interannual time scales and about 20-25% at decadal time scales. In terms of volume transport, these variabilities are associated with an AMOC standard deviation of about 0.8 Sv and 0.2 Sv, respectively. This time scale separation between forced and intrinsic variability echoes the differences in spectral properties between the leading modes of forced and intrinsic AMOC variability discussed earlier (Section 3).

To shed light on such a potential connection between the temporal variability at 26.5°N and the leading mode of AMOC variability, we have regressed the AMOC signals in the latitude-depth space onto the the time series at 26.5°N (Fig. 4). The forced ocean response at the RAPID location is associated with positively correlated anomalies from 10°S to 45°N intensified between 1000 and 2000 meters, and negatively correlated anomalies elsewhere. This spatial pattern strongly resembles the first EOF of the forced signal (Fig. 2), with a correlation factor of $r = 0.81$ between associated time series. Similarly, the regression pattern for the intrinsic AMOC variability at 26.5°N resembles the first EOF of the intrinsic signal (Fig. 2), with positively correlated anomalies from 10°S to about 35°N (Fig. 4, right panel), and a correlation factor of $r = 0.68$ between associated time series. The similarities between regression maps and EOFs strongly suggest that the temporal variability at 26.5°N is part of a spatially distributed North Atlantic structure, with both intrinsic and forced origins that mostly differ by their spectral properties.

5 Conclusion

We have discussed here the results of an ensemble-based examination of the Atlantic Meridional Overturning Circulation (AMOC) variability at low-frequency (2-30 years) and we have identified the dominant spatio-temporal patterns of variability when mesoscale ocean eddies are resolved. Our results suggest that a significant fraction of the AMOC variability is sensitive to initial conditions, or in other words, is 'chaotic'. The contribution of such a chaos is found to exceed 50% in the Gulf Stream region, and to 40-50% at the RAPID location. By extracting the leading modes of variability through Principal Component Analysis, we have revealed the presence of a basin scale mode of intrinsic AMOC variability in the North Atlantic. The variability of this intrinsic mode peaks at interannual time scales, and its spatial pattern resemble the mode of AMOC variability locally forced by the atmosphere. These results extend in the latitude-depth space earlier investigations of intrinsically versus forced AMOC variability performed by Grégorio et al. (2015) and Leroux et al. (2018) for a given depth.

We also compared our model output with the RAPID-MOCHA-WBTS program for which continuous measurements of the AMOC at 26.5°N are performed since 2004 (McCarthy et al., 2015). At low-frequency, the dominant observed trend in the left panel of Fig. 3 is the 2-3 Sv AMOC transport downturn interpreted by Smeed et al. (2014) as a result of mid-ocean geostrophic dynamics. Our simulations do not capture this over the 2005-2011 timeframe. Moreover, we do not obtain intrinsic low-frequency variability this large; our low-frequency fluctuation estimates are more like ∼0.2 Sv. The observed downturn can thus not be attributed to local intrinsic variability only, although our estimate remains in the range of long-term AMOC forced trends simulated by climate models (Caesar et al., 2018). However, we also emphasize our results are limited to intrinsic variability of North Atlantic origin. We focus here on one ensemble, but have others where boundary conditions are varying. Their analyses, not detailed here, suggest the downturn originates perhaps in the Labrador (Jackson et al., 2016) or Nordic Seas, with an unknown forced or intrinsic origin.

The simulated and observed signals agree fairly well in the high frequency band, where predominant AMOC variations of ∼O(1 Sv) of the observed signal are consistently captured by the ensemble mean. We have found the leading forced EOF peaks at 2-3 years, and interpret this as atmospherically forced AMOC interannual variability. This is consistent with the previous interpretation of the 2009-2010 event as atmospherically forced (Roberts et al., 2013). We note that all members are not phase locked to the atmosphere because of the intrinsic dynamic of the ocean, with a contribution ($\sigma_I^{HF} = 0.8$ Sv) that equals the forced signal at interannual time scales. Equivalently, a significant fraction of the interannual AMOC variability at 26.5°N is chaotic, and thus the RAPID timeseries represents only one possible trajectory among many. At interannual time scales, roughly half of the expected variability cannot be predicted in advance. These results provide a first estimate of the quantitative accuracy of the AMOC within numerical models. Probabilistic estimates as in Chapron et al. (2018) might well represent a useful avenue for further pursuit.

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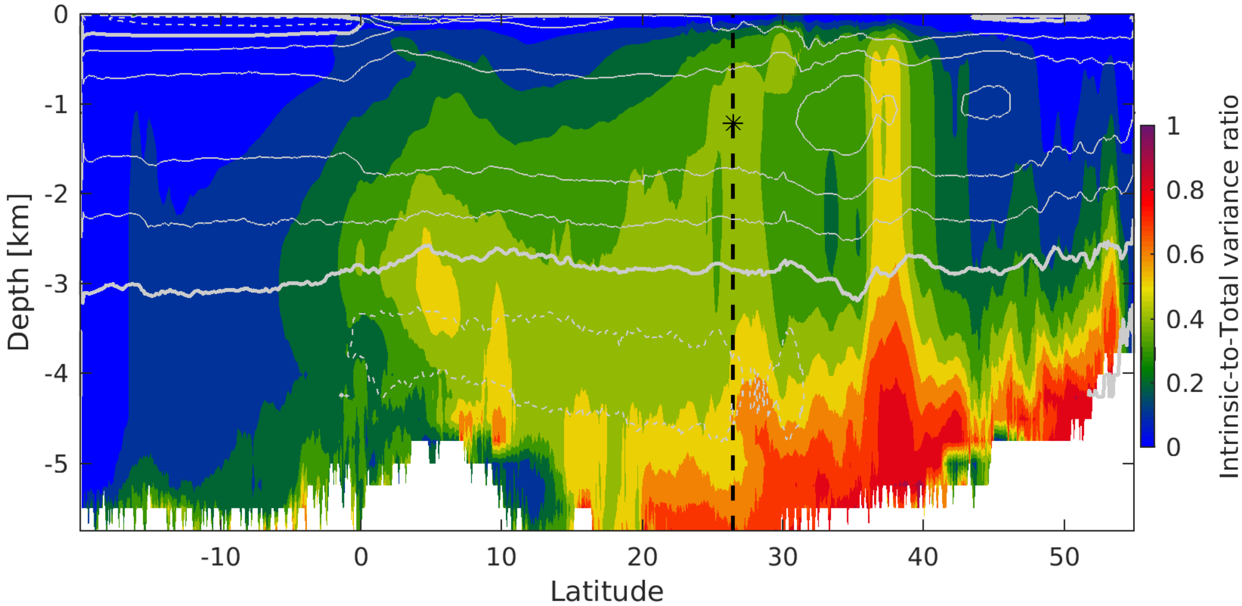

Figure 1. Intrinsic-to-total variance ratio $R = \frac{\sigma_I^2}{\sigma_T^2}$ of the simulated interannual-to-decadal AMOC variability. R indicates the fraction of the low-frequency AMOC variability that is driven by the chaotic internal ocean dynamics in the ensemble simulation (color contours every 0.1). Gray contours indicate the simulated time mean AMOC, with a contour interval of 5 Sv (1 Sv = 10^6 m^{3}s^{-1}) and a thick contour for zero values. The black dashed line represents the location of the RAPID array at 26.5°N, and the black star indicates the depth of 1200 m used in Fig. 3.

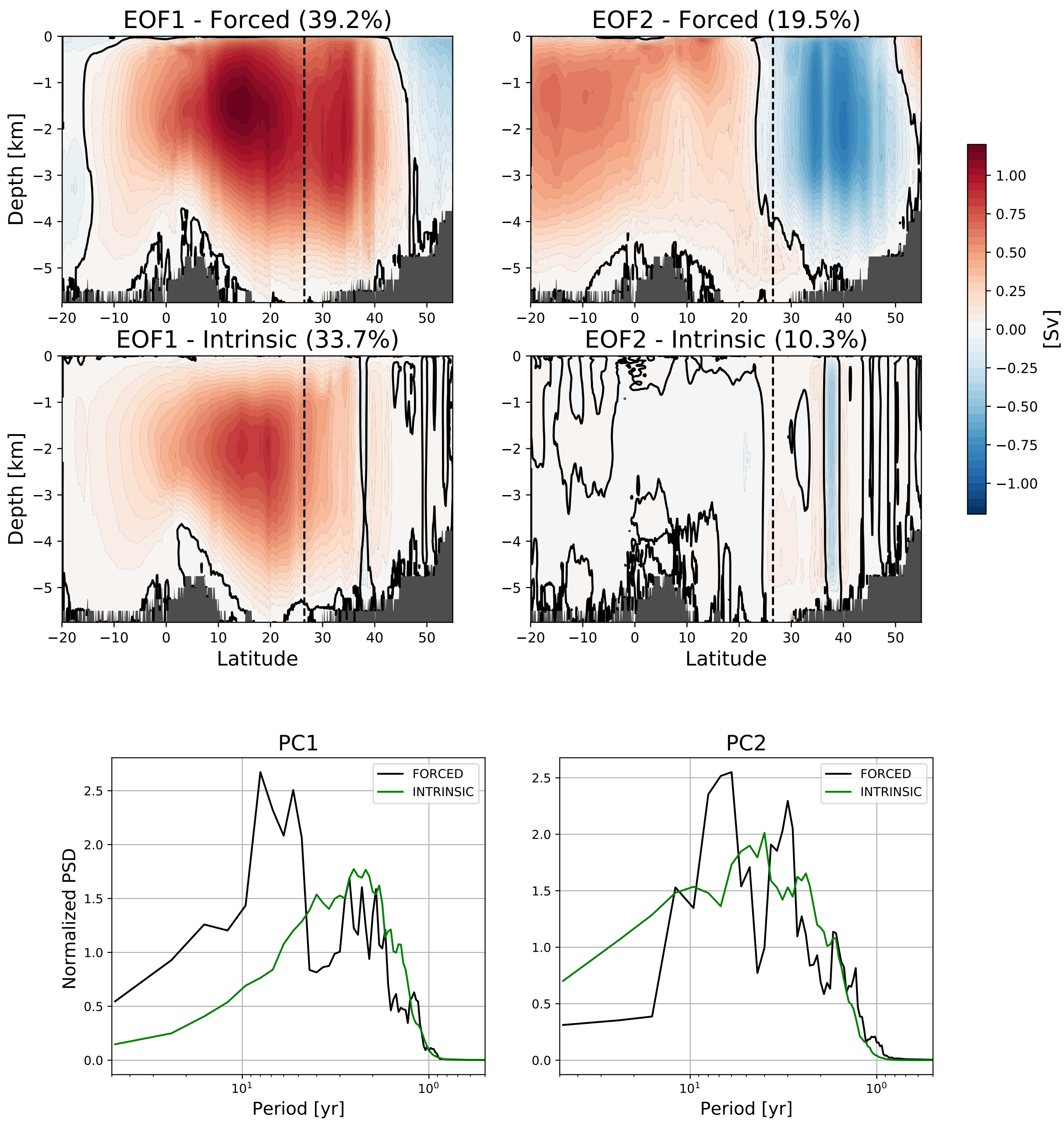

Figure 2. First (left) and second (right) Empirical Orthogonal Functions (EOFs) for the ensemble mean AMOC (top), for the intrinsic AMOC variability (middle), and the Power Spectral Density (PSD) function of the associated Principal Component (PC, bottom). The EOFs have been normalized such that they contain the amplitude in Sv of the explained signal, and the explained variance is shown on top of each panel. For the intrinsic component, the EOF and associated spectra have been computed for each individual member and then averaged together.

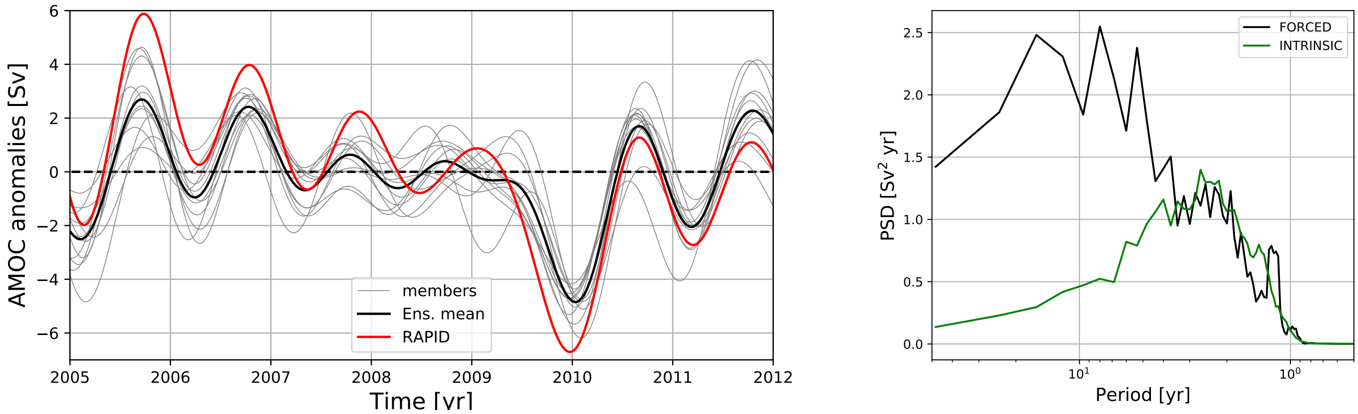

Figure 3. (Left) Time series corresponding to the variations of the northward AMOC transport, the maximum of which occurs around 1200 m depth in our model. Individual ensemble members are in light gray and the ensemble mean in black. The measured AMOC at the same depth appears in red. All data have been low-pass filtered with a cutoff at 1 year. The first and last years of data have been discarded due to side effects induced by the filter. (Right) Power Spectral Density (PSD) of the forced (black) and intrinsic (green) component of the simulated AMOC anomalies at 26.5°N and 1200 m for the 50-yr long signal. Data have been high-pass filtered and a seasonal cycle has been removed before the application of the 1-yr low-pass filter (see text for details). First and last years have been discarded due to side effects induced by the filter.

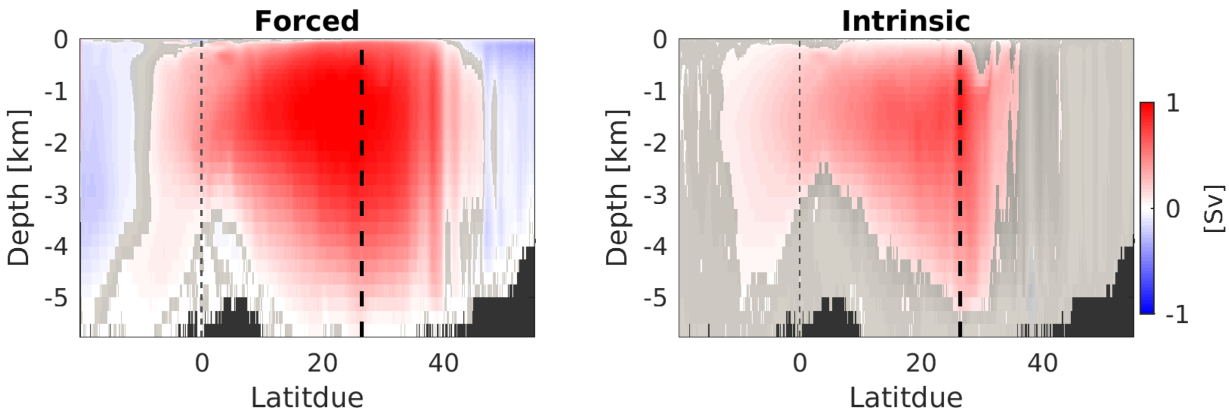

Figure 4. Regressed AMOC [Sv] in the latitude-depth space onto the AMOC time series at 26.5°N and 1200 m for the forced (left) and the intrinsic (right) component. Statistical significance has been assessed with a Monte Carlo approach by comparing the regression to that of a randomly scrambled ensemble. We have randomly permuted the AMOC time series by block of 15 days and compute a regression. This process, which aims at removing autocorrelation in the time series, is repeated 100 times. If the original regression is larger than 95% of the scrambled ensemble regressions, it is considered as statistically significant. Regressions that are not statistically significant are gray shaded. The black dashed line represents the location of the RAPID array at 26.5°N.