Signal and noise in the Atlantic Meridional Overturning Circulation at 26°N

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Abstract

The Meridional Overturning Circulation (MOC) is key to the redistribution of heat and is projected to weaken due to climate change. The RAPID mooring array observes the strength of the MOC, showing an overall weakening of 1.4 Sv/decade from 2004–2022. However, the significance of this trend is controversial. Here we consider the RAPID observations in a signal-to-noise framework to understand where low frequency, climatic signals are strongest. There is a strong signal in Lower North Atlantic Deepwater (LNADW) transports. In contrast, we find little signal and significant noise in Ekman transports. We remove the influence of the Ekman transport on MOC and LNADW estimates, reducing the noise by 30% and 22% respectively. We find a simple model of LNADW has a comparable signal-to-noise ratio as the full MOC estimate. Understanding the sources of 'noise' and 'signal' is key to timely detection of climatic change in the MOC.

Introduction

The detection of trends and climatic variations in observations of the Meridional Overturning Circulation (MOC) is an important and at times controversial topic. Reconstructions and instrumental proxy estimates for the MOC are numerous (Caesar et al. 2021) but their consistency and accuracy have been questioned (Kilbourne et al. 2022). These questions have not stopped these proxies being used to investigate critical and controversial questions such as whether the MOC maybe approaching a tipping point (Boers 2021; Ditlevsen and Ditlevsen 2023), with the latter study indicating that an MOC collapse is likely by the end of the century (Ditlevsen and Ditlevsen 2023).

Direct, continuous observations of the MOC are relatively short in the context of climatic timescales, with dedicated programmes for continuous MOC observation not beginning until the first decade of the 21st century (Frajka-Williams et al. 2019). Initial results from the RAPID-MOCHA-WBTS (hereafter RAPID) project revealed the highly variable nature of the MOC at 26°N on timescales from days to years (Cunningham et al. 2007; Kanzow et al. 2010; McCarthy et al. 2012; Smeed et al. 2014). RAPID has seen a range of -5.3 Sv [1 Sv = 106 m3 s-1] to 32.9 Sv in the MOC (10-day filtered values) from April 2004 to January 2022.

Large variability has not stopped studies looking at trends in the MOC. Smeed et al. (2014) found a weakening in the first 8 years of RAPID. The weakening MOC in the RAPID timeseries appeared to be coming to stop, with a strengthening observed until 2018 (Moat et al. 2020). However, the latest data release as of September 2023, shows a weakening signal again. Such reversals in the fortune of the MOC in the past 20 years have posed problems for the Intergovernmental Panel for Climate Change (IPCC), with a diluting in the confidence statement associated with MOC decline between the Special Report on Ocean and Cryosphere report and 6th assessment report (see McCarthy and Caesar (2023) for discussion). Understanding of the origins of the variability observed in the MOC has advanced in the 20 years of RAPID observations, with seasonality (Kanzow et al. 2010; Chidichimo et al. 2010; Pérez-Hernández et al. 2015), interannual variability (McCarthy et al. 2012; Roberts et al. 2013), and the impact of the mesoscale (Evans et al. 2022; Kanzow et al. 2009) all contributing. Surprising relationships have been unearthed such as the link between Ekman transport at the surface and lower North Atlantic Deepwater properties at 3000–5000 m (Frajka-Williams et al. 2016).

Against this highly variable background, detection of anthropogenic driven changes in the MOC has also been considered. The model study of Baehr et al. (2007) showed deep, basinwide density gradients as a sensitive estimator of MOC decline due to lower noise in the deep ocean. The importance of deep, basinwide observations was also emphasized by the climate model results of McCarthy et al. (2017). Both studies indicate the importance of deep observations in the detection of trends in the MOC.

A key motivation for sustained observations of the MOC is projection from successive generations of climate models that the MOC will weaken in response to anthropogenic climate change. The most recent CMIP6 models estimate a projected MOC weakening of 1 Sv/decade (Weijer et al. 2020). More abrupt, statistical estimates of collapse are associated with an approximate 5 Sv/decade MOC decline (Ditlevsen and Ditlevsen 2023).

In the context of detection, these low-frequency weakening (or strengthening) trends can be considered the target signal for detection of change, with other observed variability being noise. In this study, we combine our knowledge of the origins of variability in the RAPID MOC estimates in a signal-to-noise framework and consider the question of whether there are better variables than the full MOC estimate to observe climatic MOC decline.

Data and Methods

Figure 1: Monthly, deseasonalised MOC values (black) and its components (as labelled) as observed at the RAPID array.

This study uses monthly, deseasonalised¹ data from the RAPID array (Figure 1, Moat et al., 2023). Monthly averages are chosen so that each observation can be considered approximately independent. Smeed et al. (2014) found a decorrelation length scale of 40 days for the deseasonalised MOC. Using monthly, deseasonalised values, we find a similar figure of 1.5 months. The mean strength of the monthly, deseasonalised MOC is 16.8 Sv with a standard

¹ Seasonal cycle shown in Additional Information at end of this document

deviation of 3.0 Sv from April 2004 to January 2022. This is an estimate of the maximum of the overturning streamfunction—the most common metric of MOC strength.

The RAPID estimate is comprised of contributions from different components. Approximately, $AMOC \sim GS + Ekman + Therm \sim -(UNADW + LNADW),$

where GS (Gulf Stream) is the approximated by the northward flowing Florida Current (Meinen et al. 2010), Ekman Transport is the (typically) northward ageostrophic wind-driven transport in the upper 50 m, and the southwards thermocline (Therm) recirculation in the depth range 0 to 800m. These three layers constitute the majority of the upper, warm branch of the MOC. The lower, cool branch of the MOC is well-described by two southward flowing layers: Upper North Atlantic Deep Water (UNADW) from 1100 m to 3000 m, and Lower North Atlantic Deep Water (LNADW) from 3000 m.

As Figure 2 shows, the MOC can be approximately represented by the sum of upper, warm components (GS, Ekman, Therm) balanced by the deep, cold components (LNADW, UNADW). Linear regression shows this quantitively, with the upper, warm (deep, cold) components relating to the MOC with a slope of 1.0 (-1.1) and an r-squared of 0.99 (0.99). The negative MOC-NADW slope is when the MOC strengthens it results in a more positive streamfunction, whereas when the NADW transports weaken, resulting in more southward (negative) flow.

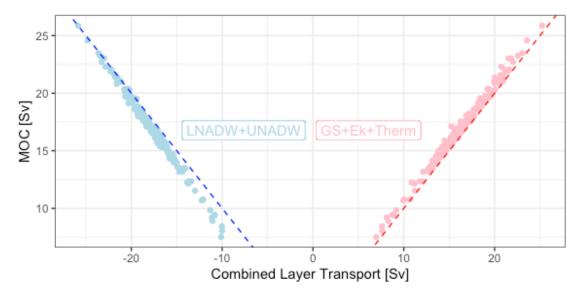


Figure 2: The relationship between the MOC, NADW, and shallow components. The deep, cold branch is approximated by the sum of UNADW and LNADW (blue dots). The warm, shallow branch is approximated by the sum of the Gulf Stream, Ekman transport, and Thermocline transport (pink dots). Lines indicating a 1:-1 and a 1:1 relationship are shown by the blue and red dashed lines respectively.

A linear fit to the MOC estimates the overall decline as 1.4 Sv/decade (Figure 3), based on deseasonalised monthly data, with fitting iterated 500 times on 50% of the datapoints (Figure 4). But is this decline significant? Statistically, we can answer this question using a linear fit, resulting in statistical significance at the 99% level. While we can categorise the statistical significance of trends, placing the climatic significance of this trend is more difficult. We cannot say that this is

the signature of externally or anthropogenically forced MOC change but we can ask when a signature of externally forced change may be detected.

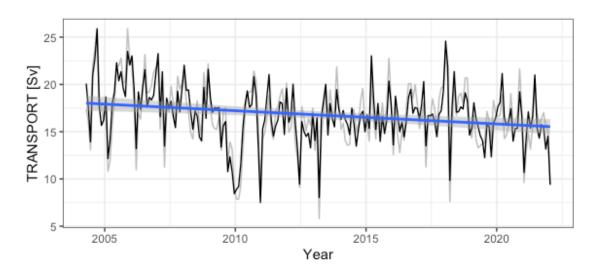


Figure 3: Linear trend in the MOC as observed at RAPID. Linear fit (blue) to the monthly, deseasonalised values (black) is shown. Monthly values with the seasonal cycle are shown in grey.

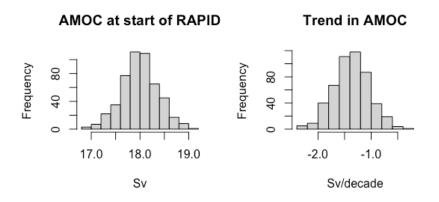


Figure 4: Estimations of the starting value (left) and trend (right) in AMOC based on linear fitting iterated 500 times on 50% of the datapoints. The mean (standard deviation) starting estimate is 18.0 Sv (0.4 Sv) with a slope (standard deviation) of 1.4 Sv/decade (0.4 Sv/decade).

One way of looking at the question of whether the MOC has changed is to consider the signal-tonoise ratio. Signal-to-noise ratio has been a useful indicator of the emergence of global climate change signals in local data (Hawkins et al. 2020; Murphy et al. 2023). Here, we apply a similar methodology to investigate the emergence of low-frequency climatic oscillations and trends in the RAPID data. We define the signal-to-noise ratio based on a linear regression model:

 $y(t)=\beta x(t)+\epsilon$

where y(t) is the observed variable, such as an individual layer transport, x(t) is our variable of interest, in this case the low-frequency MOC. In this study, we use a Loess polynomial fit over 5 years to define the low-frequency MOC. β is an unknown regression coefficient, and

$$\epsilon \sim N(0,\sigma^2),$$

where σ is the standard deviation.

There are a number of ways to consider the signal of interest. For oscillatory signals, the standard deviation of $\beta x(t)$ may be used. For emergent signals, the value of the variable of interest at a certain point may be chosen. For example, when using a signal-to-noise framework for the emergence of global temperature in local climate trends, Hawkins et al. (2020) and Murphy et al. (2023) used the end value of their variable of interest:

$$\beta x(t=t[end]),$$

in their case global mean temperature in 2018. As the MOC ends on a particularly low value in this release (9.4 Sv in the monthly, deseasonalised estimate), we choose a more conservative definition based on the trend of the MOC over the 20 years of RAPID. This allows us to define the signal as:

$\beta m \Delta t$,

where Δt is 20 years and m is the trend in variable x over the timeperiod Δt . In this case we would define the signal-to-noise ratio (SNR) as

SNR = signal/noise =(
$$\beta m \Delta t$$
)/ σ ,

where β and σ are defined as previously.

This framework lends itself to consideration of the emergence of specific trends from the noise. We can use this to define an emergence time of

$$\Delta t = (SNR \sigma)/(\beta m),$$

where m is a specified rate of decline. This timescale can be equated to a signal-to-noise ratio of 2 for 'unfamiliar' and to 3 for 'unknown' following (Frame et al. 2017).

In addition to the monthly, deaseasonalised data, we also consider certain components of the RAPID MOC estimate with Ekman transport removed. Ekman transport is calculated from wind data and incorporated to the RAPID MOC estimate directly and via a mass compensation term that ensures zero net transport across the section (McCarthy et al. 2015), which means its signal appears in the layer transports of Thermocline, AAIW, UNADW, LNADW. However, it was also found that Ekman impacts the deep density fields, and, by implication, the deep temperature and salinity (Frajka-Williams et al. 2016).

In terms of layer transports, UNADW, LNADW, and the MOC estimate itself are all significantly (p < 0.001) correlated with Ekman transport (Figure 5) with correlations of -0.32, -0.60, 0.65, respectively. Given the lack of impact of Ekman transport change on climatic timescales (Asbjørnsen and Årthun 2023; Bryden et al. 2024), to reduce the noise in the transports, we remove

the influence of Ekman transport from each layer by subtracting the regression of that layer against Ekman transport: layer_i~Ekman.

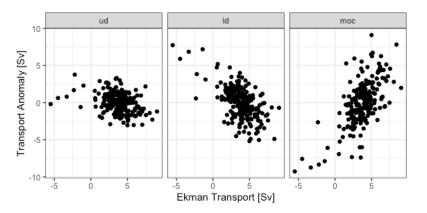


Figure 5: Components of RAPID transport with significant correlation with Ekman Transport: Upper North Atlantic Deep Water (ud), Lower North Atlantic Deep Water (ld), and the MOC.

In addition, we consider a simplified model of the LNADW transport. Worthington et al. (2021) showed that LNADW can be well described by a combination of deep density (depth = 3000 m) on the western boundary of RAPID and Ekman transport. Figure 6(a) reproduces a version of the model of Worthington et al. (2021) for the LNADW, using deep temperature and salinity instead of density:

LNADW ~ Ekman + T(z=3000m)+S(z=3000m),

where T and S are temperature and salinity respectively. This model is a good fit has an R-squared value of 0.75.

We also consider this model with the influence of Ekman transport removed. We first remove the influence of Ekman transport of the LNADW, temperature and salinity via linear regression and then model the LNADW transport as:

LNADW (no Ekman) ~ T(no Ekman,z=3000m)+S(no Ekman,z=3000m).

The results of this model are shown in Figure 6(b). This model has an R-squared value of 0.6.

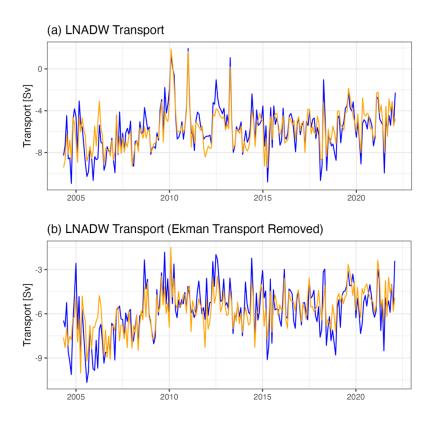


Figure 6: Models of LNADW. (a) LNADW transport (blue) and LNADW transport estimated from a linear combination of Ekman transport, temperature and salinity at 3000 m on the western boundary of the RAPID array. (b) LNADW transport with Ekman transport removed by linear regression (blue) and LNADW transport estimated from a linear combination of temperature and salinity at 3000 m on the western boundary of the RAPID array, when Ekman transport had been removed from temperature and salinity via linear regression.

Results

The figure below shows estimation of signal and noise for the MOC and its components in the RAPID data. The low-frequency MOC signal (Figure 7a), shows the decline, recovery, decline pattern and the overall decline of 1.4 Sv/decade is shown. From 2004–2022, this overall decline only begins to emerge from the 1 s.d. envelope shown. This can be considered the 'familiar' envelope, with 'unfamiliar' emerging at 2 s.d. The reflection of this low-frequency MOC signal is shown in the other panels of this figure. The MOC, Thermocline, and LNADW components have low frequency signatures that emerge from the 1 s.d. envelope (Figure 7a, d, f). The LNADW trend is reversed as it is inverse to the MOC i.e. when the MOC weakens it results in less northward flow whereas when the LNADW weakens it results in less southwards flow. The Ekman, GS, and UNADW components do not emerge from the 1 s.d. envelope, reflecting these components not carrying the signature of the low-frequency MOC (Figure 7b, c, e). Figure 7g, h, i show the effect of removal of the Ekman transport from the MOC, LNADW, and temperature/salinity derived LNADW. Each of these variables continues to reflect the low-frequency MOC signal but with lowered levels of noise.

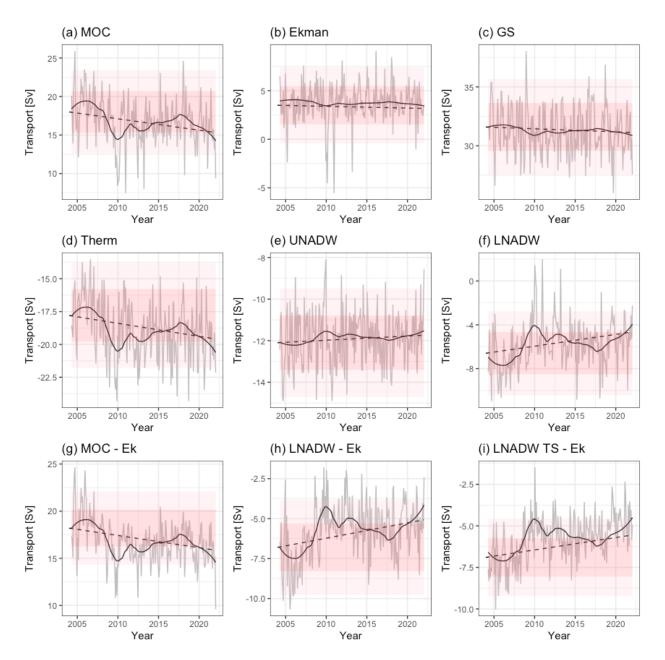


Figure 7: Signal-to-noise in components of the transport at the RAPID array at $26^{\circ}N$. (a) Monthly, deseasonalised MOC estimates (grey), low-frequency MOC signal (black) found by fitting a 5-year Loess filter, and trendline (black, dashed) estimated from linear regression iterated 500 times on 50% of the data. For each layer (b)–(f) Ekman, Gulf Stream, Thermocline, Upper and Lower North Atlantic Deep Water, the monthly, deseasonalised values (grey) were regressed against the low-frequency MOC (black line in a), with the result shown with the black solid line. Panels (g)–(i) show the same but with the Ekman transport removed for MOC, Lower North Atlantic Deep Water, and the LNADW estimated from temperature and salinity on the western boundary at 3000 m. The light and dark pink envelopes indicate 'noise' estimates for each component at the 2 and 1 s.d. levels.

The signal, noise, and signal-to-noise ratio for the MOC and its components are shown in Table 1. The signals for each are based on the overall trend of the MOC reflected in each component considered over 20 years. The largest signals are for the MOC and MOC - Ek components of 2.96 and 2.6 Sv respectively. LNADW and Thermocline components have the next largest signals at 2.16 and 1.98 Sv respectively. Lowest signals are in the Gulf Stream, UNADW, and Ekman components. Noise levels are highest in the MOC component, which is not surprising as it is an integrated measure of all layers together. The Ekman contribution, which has little signal (0.36 Sv) but a noise level of almost 2 Sv.

When signal and noise are combined, the components with the Ekman transport removed have the highest values. While signal in the MOC component has reduced by 0.36 Sv by removing Ekman transport, the noise has decreased by 0.74 Sv or almost 30%, increasing the signal-to-noise ratio to 1.34. The MOC itself is the component with highest signal-to-noise ratio. However, improvements to the signal-to-noise ratio are also evident in both LNADW components. The noise component for the LNADW dropped by 0.43 Sv or 22% to 1.49 Sv. The LNADW TS estimate shows a lower signal of 1.5 Sv but also lower noise of 1.16 Sv, giving a signal-to-noise ratio of 1.29. Given that this model is simply based on temperature and salinity at a single point on the western boundary of 26°N at 3000 m depth, our results reflect how much of the low-frequency MOC signal is present in the deep hydrography.

Considering the components that have not had Ekman transport removed, the LNADW component has a higher signal-to-noise ration that the MOC, which indicates that these deep transports may be better at detecting the climatic MOC. Other components have much lower signal-to-noise ratios. The thermocline component, which estimates the southward flow in the upper 1000 m of the ocean, was the component that the decline in the first 8 years of RAPID was mainly attributed to. It has a signal-to-noise ratio of 0.99. All the other components (Florida Current, AAIW, UNADW, and the aforementioned Ekman transport) have signal-to-noise ratios of less than 0.3.

Overall, the signal-to-noise ratio for all components considered in Table 1 is low and noise swamps the low-frequency MOC signal. A maximum signal-to-noise ratio not larger than 0.5 is indicative of a noise dominated regime. To contrast, a signal-to-noise ratio of 5 is considered a clean signal in signal processing. These values are also lower than the 'unfamiliar' (SNR > 2) or 'unknown' (SNR > 3) thresholds (Frame et al. 2017).

Each of these layer transports has a scaling factor (β) to the MOC itself. Estimates of the MOC itself are by definition close to 1. Deviations from 1 are due to either the removal of Ekman transport or skews in the relationship of the monthly to the low-frequency MOC data. Negative scale factors are shown for lower and upper North Atlantic Deep Water due to the fact that a weakening in MOC is less northward transport is reflected in these layers as less southward transport. There is also a dilution of the MOC signal in certain components. The LNADW based on temperature and salinity with Ekman transport removed has a scale factor of -0.53, showing that trends in this layer are half those of the low-frequency MOC.

We can use these values to estimate when the current trend of 1.4 Sv/decade would result in values that are either unfamiliar or unknown in the definition of Frame et al. (2017). The components with the Ekman transport removed would hit unfamiliar (unknown) around the mid-2030s (2050). Not reducing the noise by removing Ekman transport pushes this threshold back by 5 (10) years at best. Certain components will not hit these thresholds this century, based on our analysis.

	Signal [Sv]	Noise [Sv]	S to N Ratio	Scale Factor	Unfamiliar [Year]	Unkown [Year]
MOC - Ek	2.60	1.94	1.34	0.93	2034	2049
LNADW - Ek	1.92	1.49	1.29	-0.68	2035	2051
LNADW TS - Ek	1.50	1.16	1.29	-0.53	2035	2051
LNADW	2.16	1.92	1.12	-0.77	2040	2057
MOC	2.96	2.68	1.10	1.06	2040	2058
Therm	1.98	2.00	0.99	0.71	2044	2064
UNADW	0.40	1.30	0.31	-0.14	2135	2200
GS	0.52	2.03	0.26	0.19	2159	2237
Ekman	0.36	1.96	0.18	0.13	2220	2328

Table 1: Signal and noise components for MOC, its layer transports, and certain transports with Ekman removed

Discussion

In this paper, we have considered observed MOC change in a signal-to-noise framework. The MOC, as observed by the RAPID array, can be considered with its component parts including Ekman transport, Gulf Stream and thermocline transport, upper and lower North Atlantic Deepwater. Low-frequency variability or multi-year variability has been discussed in the RAPID observations by Smeed et al. (2014), who reported an MOC decline in the 8 years from 2004, and (Moat et al. 2020), who reported a stronger MOC from 2014–2018 than previously. In this latest release of the RAPID data to January 2022, the MOC has weakened steadily since late 2017 (Figure 6 a). Given the context of multi-year reversals in MOC trends since the beginning of RAPID observations in 2004, the first explanation for this latest downturn must be natural Atlantic multi-year variability (Roberts et al. 2014).

We have considered what would be a notable change in MOC using the language of 'signal' and 'noise' following similar studies of climate data e.g. (Hawkins et al. 2020; Murphy et al. 2023). In this context, we estimate noise as the standard deviations of residuals from a low-frequency MOC signal, using the language of 'unfamiliar' and 'unknown' for signals that are 2 and 3 standard deviations from a baseline respectively. In comparison with these studies, of the emergence of global temperature trends in local observations, there are a number of very different challenges for the MOC.

Firstly, choosing a baseline or starting point is far more challenging. Studies of global temperature can employ standard definitions of pre- or early-industrial period of 1850–1900. The same is not possible for MOC which does not have direct, continuous observations prior to the 21st century. In this study, we have considered a starting point based on linear fit to the full data. The period of 2004–2008 was shown by (Smeed et al. 2018) to be have a significantly stronger MOC than the period 2008–2017 so simply choosing an initial year or few years, leads to a potential high bias. In spite of the subsequent recovery of the MOC (Moat et al., 2020), our results show values of MOC and LNADW reaching weak points in January 2022—the end of the RAPID timeseries at time of writing. The more conservative baseline of beginning of a linear trend was chosen to address the question: if the MOC does decline due to climate change, when can we start to see this in observations?

Secondly, the definition of the 'signal' is not straight forward. A choice must be made about the level of smoothing applied to data. We have used a 5 year Loess polynomial fitted to the MOC data as an estimate of low frequency variations. This is a longer smoothing interval than that used by Smeed et al. (2018) of 2 years. We repeated our analysis with this shorter smoothing interval, which results in more values approaching the 'unfamiliar' envelope. For example, the MOC slowdown in 2009–2010 (McCarthy et al. 2012), becomes 'unfamiliar' with this smoothing. On the other hand, increasing the smoothing interval to 10 years yields qualitatively similar results to the 5 year window. To calculate the final value for the emergent signal, we choose the value of the linear trend in the MOC over a 20 year period beginning at the start of RAPID in 2004.

Results highlight the lack of signal and high noise in the Ekman transport and motivated the removal of the fingerprint of Ekman transport from correlated variables. This was successful and significantly reduced the noise, thus improving variables' utility for detecting climatic change. The question could be asked whether more signal may appear in the Ekman component in the future due to changing wind patterns, potentially linked to climate change. This is not supported by climate model analysis and studies have shown that Ekman transports contributes little to future MOC decline (Asbjørnsen and Årthun 2023; Bryden et al. 2024). This is not to say that wind will have no effect on future MOC, as changes may well manifest in wind-driven components such as the Gulf Stream.

The manifestation of low-frequency MOC change in MOC components may seem obvious: the components sum to give the MOC strength and so there must be a relationship. It is therefore surprising perhaps that the Florida Current and UNADW showed little of this low-frequency MOC signal. LNADW proved a sensitive indicator of low-frequency MOC change. Using the simple model derived from Worthington et al. (2021), we were able to recover much of the low-frequency MOC signal in the deep temperature and salinity at the western boundary. This is a powerful result: the full MOC estimate require multiple moorings across the Atlantic; this deep temperature and salinity are derived from a single location. This shows the importance of deep hydrographic properties in understanding and detecting MOC change. While a powerful result, it is perhaps not a surprising one: deep density was highlighted as a sensitive indicator of MOC change by Baehr et al. (2007) in a modelling study shortly after RAPID began.

The utility of deep hydrography in the detection of MOC change does come with a caveat that, in our analysis, the MOC signal is diluted when looking at its manifestation in the LNADW by a factor of 0.7 in the full LNADW transports and by 0.5 in the LNADW based on deep temperature and salinity (Ekman removed in both cases). This poses a challenge as a climatic MOC signal may be small. For example, assuming the Atlantic multidecadal variability in sea surface temperatures is linked to the MOC, combined with the scaling of 4 Sv/°C relation between MOC and Atlantic SSTs from Caesar et al. (2018), the signal would be 0.5°C over 2 decades or a 1 Sv signal. This is already close to the limits of hydrographic accuracy. McCarthy et al. (2015) showed that the absolute accuracy of 0.8 Sv (0.6 Sv) for the 10-day (annual) MOC estimates. Our simple model of LNADW based on temperature and salinity here shows a similar sensitivity. Temperature changes of 0.03°C or salinity changes of 0.004 at 3000 m on the western boundary are sufficient to change the estimate of LNADW by 1 Sv. This poses a real challenge, in particular, for salinity calibration as the target accuracy for salinity is 0.003 (temperature calibration has a target accuracy of 0.002°C). This poses a challenge for detection of changes in our current framework and also for extension of our methodology back in time when salinity calibration is even less robust.

We asked a question at the start of this manuscript of whether the 1.4 Sv/decade weakening trend in the RAPID MOC was significant, which in the language of signal and noise, would be better framed as asking whether the weakening resulted in 'unfamiliar' or 'unknown' MOC levels. The answer to both is 'no'. We have shown that even in the sensitive estimators of MOC change— MOC and LNADW with Ekman noise removed—'unfamiliar' ('unknown') levels won't be reached by this trend, if it continues, until around the mid-2030s (2050). The framework of signal and noise also allows us to consider when larger trends, were they to occur, would emerge from the noise. For example, the trend in MOC since 2018 has followed a 5 Sv/year weakening trajectory. This rate of decline is consistent with the mid-21st century collapse of the MOC discussed by Ditlevsen and Ditlevsen (2023). Were this to continue, unfamiliar values of MOC would emerge in around 4 years, given an estimated noise level of 2 Sv in MOC values when seasonality and Ekman influence is removed. In other words, if this extreme scenario were to occur, RAPID would detect it by the end of the decade.

Conclusions

We have considered observed MOC change at the RAPID array in a signal-to-noise framework and conclude that we have yet to see MOC values that are 'unfamiliar' or much less 'unknown'. We have explored the sensitivity of observations in the RAPID array to detection of signals and emphasise the importance of removing those components that carry much noise and little signal such as Ekman transport. In our framework, the overall trend from RAPID of 1.4 Sv/decade, which is close to the 1 Sv/decade estimate of future MOC weakening from climate models (Weijer et al., 2020), will result in unfamiliar values by the mid-2030s and unknown values by 2050.

Our confidence in these future climate projections is typically based on a climate model's ability to reproduce the past—something that climate models are not so good at for MOC (McCarthy and Caesar 2023)—and that past MOC strength is a controversial topic in its own right (Caesar et al. 2021; Kilbourne et al. 2022). Whether or not the MOC has been declining overall since the mid-20th century depends heavily on whether or not the MOC was stronger in the first half of the 20th century (Caesar et al. 2021). In this study, we have highlighted the potential for deep hydrography, near the western boundary of the Atlantic to provide a sensitive estimate of low-frequency MOC variations and offers the potential to reconstruct the MOC in the past, although challenges around calibration remain. Nonetheless, the challenge in detecting climatic change in the MOC is large. The noise is large and the signal may be small. This emphasizes the importance of high quality direct observations of the MOC such as those provided by RAPID since 2004, not only as a tool for monitoring the MOC in the present but also for understanding the past and contextualising future changes.

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Additional Information

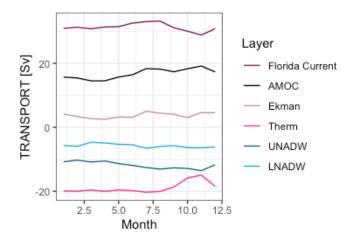


Figure 8: The seasonal cycle of the MOC and its components as observed by the RAPID array.