Impact of daily fluctuations on long-term predictability of the Atlantic meridional overturning circulation

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[1] The first continuous assessment of the Atlantic meridional overturning circulation (MOC) indicates strong MOC variability on time scales of about a few weeks. A large part of this variability results from, or is related to, wind stress forcing, which is not predictable beyond a few weeks. The presence of short-term MOC fluctuations could significantly limit long-term MOC predictability which owes its potential to the slow components in ocean dynamics. To quantify this limitation, two null hypotheses that address not only the existence but also the strength of slow dynamics are tested. Daily and yearly MOC time series generated by the ECHAM5/MPI-OM model are used for this purpose. The tests compare the variance generated by slow dynamics with that of short-terms fluctuations that extend into low frequencies. The comparison is done for total variances as well as for variances within different low-frequency ranges. It is found that the model's slow dynamics become noticeable only on time scales longer than three years. The variance generated by the slow dynamics dominate that related to the low-frequency extension of unpredictable noise only on time scales longer than 10 years. In order to utilize the potential predictability originating from slow processes, a prediction should correctly capture slow processes in the initial state by assimilating observations over a period of at least three years. **Citation:** von Storch, J.-S., and H. Haak (2008), Impact of daily fluctuations on long-term predictability of the Atlantic meridional overturning circulation, *Geophys. Res. Lett.*, *35*, L01609, doi:10.1029/2007GL032385.

1. Introduction

[2] Variations of the North Atlantic Meridional Overturning Circulation (MOC) can significantly affect climate. Based on continuous observations within the framework of the UK Rapid Climate Change (RAPID) Program, daily estimates of the MOC at 26°N have become available [*Cunningham et al.*, 2007]. According to these estimates, it is not uncommon to observe MOC changes of the order of 10 Sv within one to two weeks. The Atlantic MOC varies hence not only on long (e.g. decadal to multidecadal time scales) but also on much shorter time scales with much larger amplitudes. The daily variations are driven partly by surface wind stress and partly by density differences. Since these fluctuations are not predictable beyond a lead time of a week or so, their existence poses a challenge for MOC prediction as an initial value problem.

[3] So far various modeling studies have suggested that the Atlantic MOC varies on decadal to multidecadal time scales [e.g., *Weaver and Sarachik*, 1991; *Delworth et al.*, 1993; *Cheng et al.*, 2004]. If there is no strong intra-seasonal variability, any prediction starting from a point on the slow trajectory of the MOC would possess a notable skill, simply due to the inertia of slow variations. Several studies using ensemble coupled prediction experiments [*Griffies and Bryan*, 1997; *Pohlmann et al.*, 2004; *Collins et al.*, 2006; *Latif et al.*, 2006] indeed demonstrated impressive long-term predictability. However, all these experiments were initialized with perturbed atmospheric conditions, but unperturbed oceanic conditions. In the light of strong short-term MOC fluctuations, the use of perfect ocean initial conditions could lead to much too optimistic results. This is because, by starting from 'perfect' ocean initial conditions, one neglects the difficulty in correctly identifying the track of the slow component and the position on the slow track from which the prediction is performed. In practice, such an identification could be challenging, if not impossible, due to concealment through strong short-term fluctuations. If this happens, the existence of decadal and interdecadal MOC variations alone may not be sufficient for making skillful long-term MOC predictions.

[4] Given the observational evidence of strong intra-seasonal MOC variations, there is a need to study their impact on the long-term MOC predictability. Such impacts are studied here using yearly and daily MOC time series obtained from a coupled atmosphere-ocean general circulation model. The method used is the standard one-way analysis of variance (ANOVA) [see, e.g., *von Storch and Zwiers*, 1999, section 9.2]. However, the present analysis is concerned not only with the existence of a slow component that could facilitate a long-term MOC prediction, as in the previous ANOVA applications. More importantly, the analysis also addresses the question of whether or not the slow component is strong enough to be practically predictable in the face of unpredictable short-term components.

2. Data

[5] The MOC time series to be analyzed are obtained from integrations with the coupled ECHAM5/MPI-OM model developed at the MPI for Meteorology in Hamburg [*Roeckner et al.*, 2003; *Jungclaus et al.*, 2006]. The model was used to perform scenario integrations for the IPCC fourth assessment report. The integrations consist of three 130-year simulations forced by the observed greenhouse gas concentration from 1880 to 1999 and continued with the

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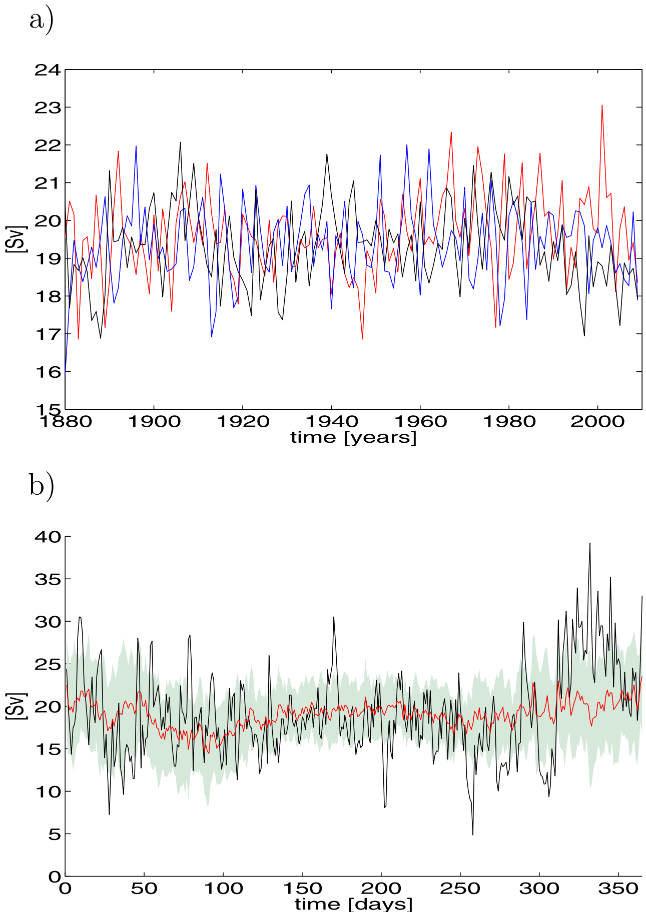

Figure 1. MOC time series: (a) three 130-year realizations of yearly MOC time series, and (b) the mean averaged over 22 years (red) and ± one standard deviation (shading) of daily MOC deviations from the mean. The typical daily variations are indicated by the daily time series for an arbitrary year in Figure 1b (black line).

IPCC A1B scenario from 2000 to 2009. The experiments differ only in their initial conditions. Since the greenhouse gas concentration changes only moderately from 1880 to 2009, its effect on the Atlantic MOC is small, as suggested by an inspection of the yearly MOC time series (Figure 1a). Unfortunately the oceanic outputs originally were not stored on a daily basis. In order to assess the role of daily variations, the coupled model was rerun for the period 1924 to 1945. Daily ocean velocities were stored and daily MOC values were calculated.

[6] In the following, the Atlantic MOC is described by the maximum of zonally averaged meridional overturning streamfunction at 26°N below 1000 meter (for the model time-mean overturning streamfunction see Figure 6 by *Jungclaus et al.* [2006]). The maximum overturning represents the total northward volume transport across 26°N. Not only density driven but also wind driven flows contribute to this transport.

[7] In summary, three 130-year yearly MOC time series and 22 years daily MOC time series are available. Apart from removing a mean annual cycle from the daily data, obtained by averaging over 22 years of daily data, no further treatment is made.

3. Method

3.1. ANOVA and Two Different Null Hypotheses

[8] The standard one-way ANOVA is based on the assumption that a climate variable x, in the present case the MOC, can be decomposed into a slow component s, which results from some slow external forcing or slow internal dynamics, and a fast component f, which originates from noise. The slow component s constitutes the potentially predictable part of x, whereas f is not predictable. Averaging x over time τ, which is shorter than the characteristic time scale of s, one obtains

$$\overline{x}_i = s_i + \overline{f}_i, i = 1, \cdots, I, \tag{1}$$

where the overbar indicates the average over time period τ. Hereafter, τ is set to one year which is much shorter than the expected time scales of the slow component. i indexes years and I is the total number of years. Assuming that s is independent of f, equation (1) implies that the variance of $\bar{x}$, $\sigma_{\bar{x}}^2$, can be written as the sum of the variances of s and f, $\sigma_s^2+\sigma_{\bar{x}}^2$.

[9] To obtain an estimate of $\sigma_{\bar{x}}^2$ from a time series, we follow *von Storch and Zwiers* [1999, paragraph 17.2.3] and determine $\sigma_{\bar{x}}^2$ by 'inter-chunk' variability

$$\hat{\sigma}_{\bar{x}}^2 = \frac{1}{I-1}\sum_{i=1}^{I}\left(\overline{x_i} - \overline{\overline{x}}\right)^2 \tag{2}$$

with $\overline{\overline{x}}$ being the overall time mean. $\sigma_{\bar{f}}^2$ is estimated by

$$\hat{\sigma}_{\bar{f}}^2 = \frac{1}{2\tau}\hat{\Gamma}\left(\frac{1}{\tau}\right), \tag{3}$$

where $\hat{\Gamma}(\frac{1}{\tau})$ is the chunk estimate of the spectral value at the lowest frequency $1/\tau$ within a chunk of length τ. Hereafter $\hat{}$ denotes an estimator or a test statistic as a random variable. $1/2\tau$ is the length of the frequency interval $(0, 1/2\tau]$ over which the variance of $\bar{x}$ is distributed. The spectral approach is based on the idea that although f varies on short time scales, it always has a white-noise extension over low frequencies. This low-frequency white-noise (LFWN) extension of f, as estimated by equation (3), forms the unpredictable part of the low frequency variance of x [*Madden*, 1976]. Having obtained $\hat{\sigma}_{\bar{x}}^2$ and $\hat{\sigma}_{\bar{f}}^2$, σ_s^2 is estimated by $\hat{\sigma}_{\bar{x}}^2 - \hat{\sigma}_{\bar{f}}^2$.

[10] Previous predictability studies have concentrated on the existence of the slow component s [e.g., *Madden*, 1976; *Rowell et al.*, 1995; *Rowell*, 1998; *Zwiers*, 1996; *Boer*, 2004; *Pohlmann et al.*, 2004]. The existence of s is assessed by testing the null hypothesis

$$H_1 : P_1 = \frac{\sigma_{\bar{x}}^2}{\sigma_{\bar{f}}^2} = 1, \tag{4}$$

H_1 is equivalent to $\sigma_s^2 = 0$, or to $\sigma_s^2/\sigma_{\bar{x}}^2 = 0$. P_1 compares the variance of x over the low frequency range $(0, 1/2\tau]$ with the variance associated with the LFWN extension of f over the same frequency range. Rejecting H_1 using one-sided test suggests the existence of the slow component.

Table 1. ANOVA Result[a]

	MOC	MOC-Ekman
$\hat{\sigma}_{\bar{f}}^2$	0.73	0.16
$\hat{\sigma}_{\bar{x}}^2$	1.13	0.96
$\hat{\sigma}_{s}^2$	0.40	0.80
$\hat{P}_1$	1.55 (1.50)	5.91 (1.50)
$\hat{P}_2$	0.55 (2.00)	4.91 (2.00)

[a] $\hat{\sigma}_{\bar{f}}^2$ and $\hat{\sigma}_{\bar{x}}^2$ are estimates of the variance originating from unpredictable daily fluctuations and the total variance of yearly MOC time series. $\hat{\sigma}_s^2$ equals $\hat{\sigma}_{\bar{x}}^2 - \hat{\sigma}_{\bar{f}}^2$. The test statistics $\hat{P}_1$ and $\hat{P}_2$ are given by $\hat{\sigma}_{\bar{x}}^2/\hat{\sigma}_{\bar{f}}^2$ and $\hat{\sigma}_s^2/\hat{\sigma}_{\bar{f}}^2$, respectively. Values in the brackets are critical values at 5% significance level. To obtain those associated with $\hat{P}_1$, note that $\hat{P}_1$ is F-distributed with ν_x and ν_f degrees of freedom under the null hypothesis $P_1 = 1$. Here $\nu_x = 3 \times 130$-1 and $\nu_f = 2 \times 22$ [von Storch and Zwiers, 1999, paragraph 17.2.4] are the degrees of freedom of the estimators $\hat{\sigma}_{\bar{x}}$ and $\hat{\sigma}_{\bar{f}}$, respectively. To obtain those associated with $\hat{P}_2$, note that $\hat{\sigma}_{\bar{x}}/2\hat{\sigma}_{\bar{f}}$ is F distributed under the null hypothesis $P_2 = 1$. The null hypothesis is rejected at 5% significance level, when the statistics are smaller the critical values.

[11] The existence of the slow component s forms the necessary but not sufficient condition for having real prediction skills, since a *potential* predictability can not always be turned into a *real* predictive skill. It is conceivable that a prediction is likely to fail when variations of $\bar{f}$ dominate those of s. To further quantify the degree of difficulty in turning the potential predictability into a true prediction skill, the null hypothesis

$$H_2 : P_2 = \frac{\sigma_s^2}{\sigma_{\bar{f}}^2} = P_1 - 1 = 1 \qquad (5)$$

is tested. Here we assume that the variations of s should be at least as strong as the LFWN extension of f so that s is not buried under the variations of f. Rejecting H_2 using one-sided test suggests that the variations of s are stronger than those related to the LFWN extension of the unpredictable fast component. In the following, the statistic $\hat{P}_1$ is evaluated against both H_1 and H_2.

3.2. Extension in the Frequency Domain

[12] So far the discussion concentrates on variances over the entire frequency range $\Omega_o = (0, 1/2\tau]$, over which the variance of yearly MOC time series is distributed. The analysis can be extended by considering variances within different frequency ranges. The extension under null hypothesis H_1 is described by *Rowell and Zwiers* [1999]. The extension under H_2 is given below in analogy to Rowell and Zwiers. We consider frequency ranges $\Omega_k = (0, k/(I \times \tau)]$, with $k = I/2, I/2 - 1, \cdots, 1$, to assess the situation on increasingly longer time scales. Based on the fact that the periodogram partitions the sample variance, the variance of $\bar{x}$ over the frequency range Ω_k can be estimated from

$$\hat{\sigma}_{\bar{x},\Omega_k}^2 = \frac{2}{I-1} \sum_{l=1}^{k} \sum_{n=1}^{nc_x} \hat{\Gamma}_{\bar{x},n}(\omega_l), \qquad (6)$$

where $nc_x = 3$ gives the total number of yearly time series considered. $\hat{\Gamma}_{\bar{x},n}(\omega_l)$ is the periodogram at frequency $\omega_l = l/I$, $l = 1, \cdots, k$, and computed from one of the three yearly time series.

[13] The variance associated with the LFWN extension of f over Ω_k can be estimated by

$$\hat{\sigma}_{\bar{f},\Omega_k}^2 = \frac{k}{I \times \tau} \hat{\Gamma}\left(\frac{1}{\tau}\right), \qquad (7)$$

where $\hat{\Gamma}(\frac{1}{\tau})$ is the same spectral estimate as in equation 3. $k/I \times \tau$ is the approximate length of the interval Ω_k. The variance of s over frequency range Ω_k, $\sigma_{s,\Omega k}^2$, is estimated as the difference $\hat{\sigma}_{\bar{x},\Omega_k}^2 - \hat{\sigma}_{\bar{f},\Omega_k}^2$.

[14] The existence of non-zero variations s over Ω_k is tested by the null hypothesis $H_{1,k}$: $P_{1,k} = \hat{\sigma}_{\bar{x},\Omega_k}^2/\hat{\sigma}_{\bar{f},\Omega_k}^2 = 1$, which is equivalent to $\sigma_{s,\Omega k}^2 = 0$. Rejecting $H_{1,k}$ suggests the existence of the slow variations in the frequency range Ω_k. To further quantify the degree of difficulty in turning the non-zero $\sigma_{s,\Omega k}^2$ into a true prediction skill, the null hypothesis $H_{2,k}$: $P_{2,k} = \sigma_{s,\Omega k}^2/\sigma_{\bar{f},\Omega_k}^2 = 1$ is tested. Rejecting $H_{2,k}$ indicates that the variations of s over the frequency range Ω_k dominate those related to the LFWN extension of f over the same frequency range.

[15] In summary, the consideration of $H_{1,k}$ and $H_{2,k}$ aims at the same goals as the consideration of H_1 and H_2. The only difference is that H_1 and H_2 study the situation over the entire frequency range resolved by the yearly MOC time series, while $H_{1,k}$ and $H_{2,k}$ examine the situation on increasingly longer time scales.

4. Analysis of the Impact of Daily Variations

[16] The standard deviation of the daily MOC time series produced by the ECHAM5/MPI-OM model (shading in Figure 1b) ranges from about 2.5 to 5 Sv during the northern summer to about 4 to 8 Sv during the northern winter. These values are much larger than the standard deviation of about 1 Sv obtained from the yearly time series (Figure 1a). For an individual MOC time series (black line in Figure 1b), it is not uncommon to observe changes of about 10 Sv within one to two weeks. This behavior is in broad agreement with the one year observation obtained from the UK Rapid Climate Change Program [*Cunningham et al.*, 2007].

[17] The first column of Table 1 summarizes the result found when considering the frequency interval Ω_o. The variance related to the LFWN extension of daily fluctuations is 0.7 Sv^2 which is barely 3% of the total daily variance of about 23 Sv^2 (Figure 1b). The total yearly variance is 1.1 Sv^2. About 65% of this variance is related to the LFWN extension of daily variations. The null hypothesis H_1 is just rejected at 5% significance level, suggesting the existence of slow dynamics. The null hypothesis H_2, on the contrary, cannot be rejected at 5% significance level. Variations generated by the slow dynamics are much weaker than that resulting from LFWN extension of the fast processes.

[18] What happens on time scales longer than a year? Can one then more clearly identify variations that exist in addition to the LFWN extension of f? If so, will the respective variance be larger than that associated with the LFWN extension of f? To answer these questions, $P_{1,k}$ and $P_{2,k}$ are estimated according to section 3b and the hypotheses $P_{1,k} = 1$ and $P_{2,k} = 1$ are tested.

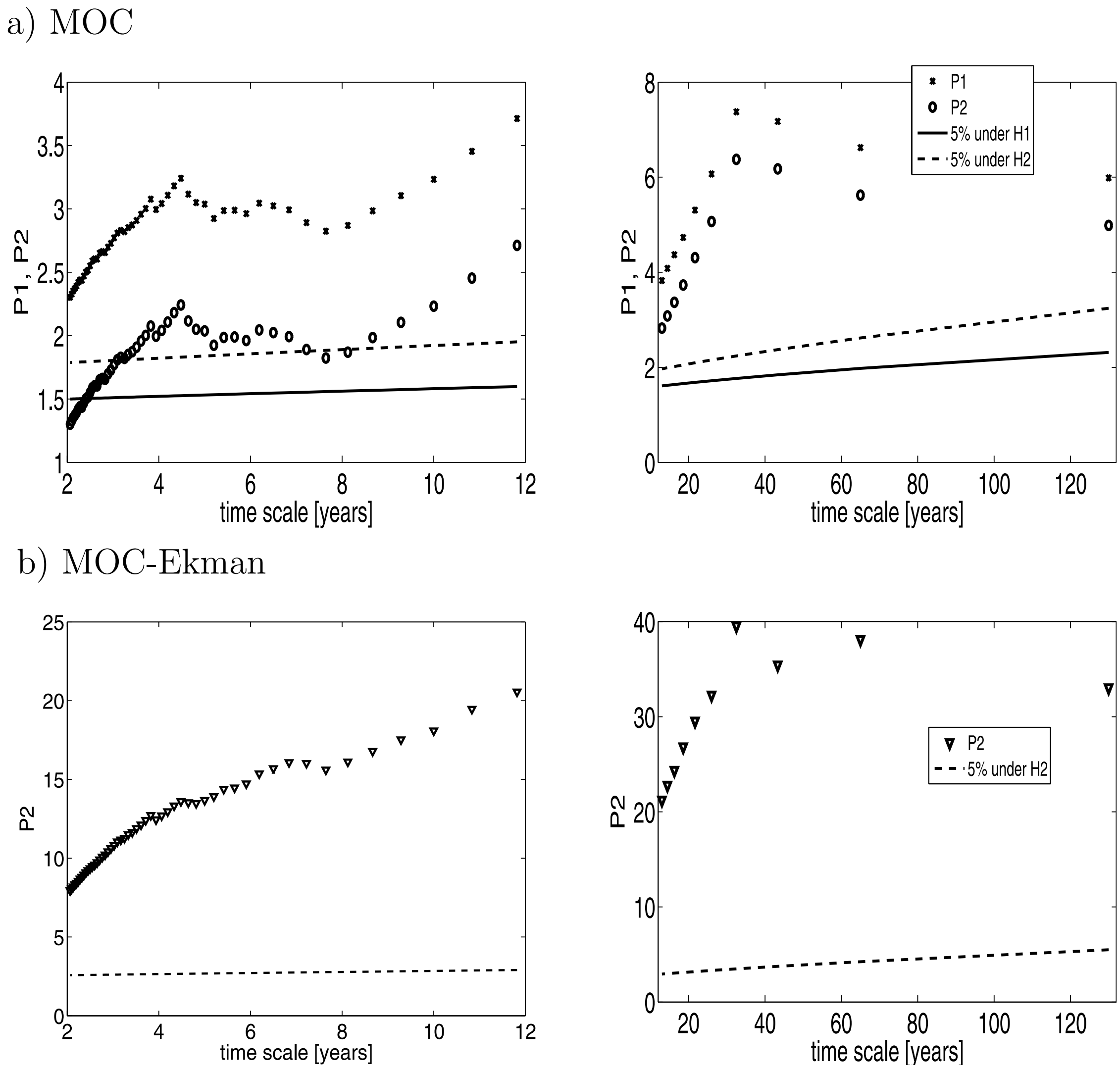

Figure 2. Statistics $\hat{P}_{1,k}$ (crosses) and $\hat{P}_{2,k}$ (open circles and triangles) as functions of time scales for (a) the MOC index and (b) the MOC index without the Ekman contribution. The time scale on the x-axis gives the smallest time scale in the frequency range Ω_k. The critical values at 5% significance level under null hypotheses $P_{1,k} = 1$ and $P_{2,k} = 1$ are shown by the solid and dashed lines, respectively. To obtain the former, note that $\hat{P}_{1,k}$ is asymptotically F-distributed with $\nu_{x,k}$ and nc_f degrees of freedom under the null hypothesis $P_{1,k} = 1$. $\nu_{x,k} = 2 \times 3 \times k$ and $nc_f = 2 \times 22$ are the degrees of freedom of the estimates of $\sigma_{\bar{x},\Omega_k}$ and $\sigma_{\bar{f},\Omega_k}$, respectively. To obtain the latter, note that $\hat{\sigma}^2_{\bar{x},\Omega_k}/2\hat{\sigma}^2_{\bar{f},\Omega_k}$ is asymptotically F-distributed under the null hypothesis $P_{2,k} = 1$. The null hypothesis is rejected at 5% significance level, when the statistics are below the critical values.

[19] Figure 2 shows that slow processes exist on all considered time scales. However, these slow processes are unable to produce significant variations on time scales shorter than about 3 years. Variations associated with slow processes remain mostly not significantly stronger than those originating from the LFWN extension on time scales between 3 and 10 years. Only on time scales longer than about 10 years, the variations of slow processes dominate those of unpredictable noise.

[20] The result suggests that although there exist slow variations in addition to the LFWN extension of f, the slow variations cannot always dominate the LFWN extension of f. Furthermore, as long as the prediction model of choice is the coupled ECHAM5/MPI-OM model, which produces not only slow MOC variations but also strong daily fluctuations, predicting MOC variations remains a difficult task. The potentially predictable component dominates the unpredictable fast component only on time scales longer than 10 years.

[21] The above result is consistent with the spectra derived from the daily and yearly MOC time series (not shown). The spectral level on time scales around 2 to 3 years is only slightly higher than the LFWN extension of the daily fluctuations, consistent with rejecting H_1 but accepting H_2. The maximum estimate of $P_{2,k}$ in Figure 2a is related to the spectral maximum near 4 to 5 years. Only on time scales longer than 30 years is the spectral level clearly higher than the LFWN extension of the daily fluctuations.

[22] What produces the strong daily MOC fluctuations in the model? The MOC time series is defined as the maxi-

mum northward transport. This transport contains contributions not only from density-driven, but also from wind-driven flows. An important part of the latter is the Ekman transport. It is conceivable that the strong daily fluctuations represent the Ekman transport resulting from daily wind stress variations. Using the zonal wind stress generated by the coupled model, the zonally averaged Ekman transport across 26°N is calculated and subtracted from the MOC time series. The procedure efficiently removes short-term fluctuations in the MOC, since high-frequency spikes in MOC coincide mostly with those in Ekman transport, similar to the observations [*Cunningham et al.*, 2007, Figure 3]. After subtracting Ekman transport from MOC, both H_1 and H_2 can be rejected with almost no risk at all (right column in Table 1). The triangles in Figure 2 show that $H_{2,k}$ can be rejected with almost no risk for all Ω_k. Consistent with this conclusion, the respective low-frequency spectrum is more than one order of magnitude higher than the LFWN extension of f (not shown).

5. Discussion and Conclusions

[23] The long-term MOC predictability is reexamined using simulated MOC data. In general, the variances generated by the model compare well with those found in the RAPID array (S. Baehr et al., manuscript in preparation, 2007). The following conclusions are drawn:

[24] (1) The simulated MOC variations can be considered as being generated by processes which have distinctly different time scales. The dominant time scale of the slow process is longer than 3 years, which is much longer than the time scale of the fast process of about a few weeks.

[25] (2) Variations generated by the slow process are well below the LFWN extension generated by the unpredictable fast processes on time scales shorter than 3 years and remain mainly below the LFWN extension on time scales between 3 to 10 years. They become only over and above the LFWN extension on time scales beyond 10 years.

[26] (3) The unpredictable fast component results mainly from the Ekman transport induced by wind stress forcing.

[27] The analysis of the present paper shows that about 65% of the variance obtained from yearly MOC time series are related to unpredictable "weather" noise. This suggests a short-term limit of the predictability of MOC. Even when all slow variations are correctly predicted by the coupled model, the prediction of yearly MOC values is still far from being perfect, as long as there is no improvement in predicting the other 65% of the variance that originates from "weather noise".

[28] The analysis has also implications for initializations of real MOC predictions. To utilize the potential predictability originating from slow processes, one should make sure that the initial condition correctly captures the states generated by the slow processes. This can be done by assimilating observations over a long period of about at least three years. By doing so, one could ensure that variations generated by slow processes, which only dominate the LFWN extension generated by fast processes on long time scales, are correctly captured in the initial condition. Generally, it can be said that achieving skills in real MOC predictions is unlikely as straightforward as suggested by previous studies [e.g., *Collins et al.*, 2006].

[29] Accepting that the wind-induced Ekman contribution is not predictable, the skill of the prediction model used lies entirely on the ability of the model in correctly representing the slow dynamics in the ocean. This ability can be assessed using data from an observational system, such as RAPID, in which the non-Ekman contribution (e.g. the part which is less affected by short-term wind forcing) is well separated from the MOC transport.

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