

Early Detection of Changes in the North Atlantic Meridional Overturning Circulation: Implications for the Design of Ocean Observation Systems

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ABSTRACT

Many climate models predict that anthropogenic greenhouse gas emissions may cause a threshold response of the North Atlantic meridional overturning circulation (MOC). These model predictions are, however, uncertain. Reducing this uncertainty can have an economic value, because it would allow for the design of more efficient risk management strategies. Early information about the MOC sensitivity to anthropogenic forcing (i.e., information that arrives before the system is committed to a threshold response) could be especially valuable. Here the focus is on one particular kind of information: the detection of anthropogenic MOC changes. It is shown that an MOC observation system based on infrequent (decadal scale) hydrographic observations may well fail in the task of early MOC change detection. This is because this system observes too infrequently and the observation errors are too large. More frequent observations and reduced observation errors would result in earlier detection. It is also shown that the economic value of information associated with a confident and early prediction of an MOC threshold response could exceed the costs of typically implemented ocean observation systems by orders of magnitude. One open challenge is to identify a feasible observation system that would enable such a confident and early MOC prediction across the range of possible MOC responses.

1. Introduction

Anthropogenic greenhouse gas emissions may trigger climatic changes with major implications for human welfare (Smith et al. 2001). The possibility of abrupt and extreme events has increasingly been a focus of

climate research. Abrupt climate change is an example of a potential high-impact event that has received considerable attention (Nordhaus 1994; Lempert et al. 1994; Keller et al. 2000, 2005, 2007b; Alley et al. 2003). One example of a potential abrupt change is the collapse of the North Atlantic meridional overturning circulation (MOC).

An MOC collapse would likely have a considerable impact on the continental climates of the North Atlantic basin (Manabe and Stouffer 1999; Vellinga and Wood 2002), where the heat transported by the MOC is an important component of regional climates (Ganachaud and Wunsch 2000). The resulting climate change may be abrupt and potentially disruptive of live-

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lihoods and economies in these regions (Tol 1998; Alley et al. 2003). In addition, climate management strategies designed to reduce the risk of an MOC collapse require higher CO₂ abatement levels than strategies that neglect a possible MOC collapse (Stocker and Schmittner 1997; Keller et al. 2000; Zickfeld and Bruckner 2003). It is, however, uncertain whether and how anthropogenic greenhouse gas emissions will affect the MOC (Cubasch and Meehl 2001; Gregory et al. 2005). Reducing the uncertainty about the MOC response can have economic value, because it can result in an improved design of climate management strategies.

Estimating the economic value of information for various environmental monitoring and prediction systems is an area of active research. Most of this work has focused on the 10-day time scale of operational weather forecasting (Johnson and Holt 1997). The seasonal-to-annual time scale has received some attention, especially with regard to El Niño–Southern Oscillation (ENSO) prediction (Solow et al. 1998). Longer time scales of a decade or more have received markedly less attention, in part because prediction uncertainties increase considerably (Knutti and Stocker 2002; Sutton and Hodson 2005; Pohlmann et al. 2004). The economic value of information about long-term climate change has been the focus of relatively few studies, even though it can be substantial because of the large spatial and temporal scales involved (Katz and Murphy 1997; Nordhaus and Popp 1997). In considering the value of an integrated, sustained ocean observation system, Adams et al. (2000) conclude that such an observation system might yield an early warning sign of an MOC collapse. They go on, “it is unknown whether any actions could be taken in response to such a warning, but if actions were possible, the value of that information would be very high” (p. 37). This is the problem we address in this study.

Here we take a step toward an improved design of MOC observing systems. In a scientific analysis, we present a simple Bayesian method for analyzing the future development of our knowledge about the MOC strength. We account for the effects of observation error, observation frequency, and random variability in the MOC intensity. We argue that a continuation of past practices of MOC observation based on infrequent hydrographic observations is unlikely to detect a model-predicted MOC collapse with high confidence within a century. This raises the possibility that we will detect MOC changes only after we have passed a forcing threshold. Earlier detection can be achieved by increasing the observation frequency or reducing the observation error. Our scientific analysis does not address the question of MOC prediction across the range of

relevant structural and parametric uncertainties, an area of open and ongoing research (Schmittner et al. 2005; Keller and McInerney 2006, manuscript submitted to *Climate Dyn.*; Challenor et al. 2006).

We put our scientific analysis into an economic perspective by estimating the economic value of information associated with an early and confident prediction of an MOC collapse. The estimated value of information would be on the order of billions of U.S. dollars. This is orders of magnitude larger than the costs of typically deployed ocean observation systems. Investments into an ocean observation system that would deliver an early and confident prediction of an MOC collapse and that would cost less than the estimated value on the order of billions of dollars would pass a cost–benefit test. These conclusions are subject to several important caveats (discussed below).

2. The North Atlantic meridional overturning circulation

The present distribution of climate zones is strongly affected by ocean circulation (Siedler et al. 2001). The MOC, which transports large amounts of heat from the Tropics to the polar regions, consists of a fairly shallow wind-driven component and a deeper, buoyancy-driven component known as the thermohaline circulation (THC). The THC is driven by fluxes of heat and freshwater across the air–sea interface, which alter the density of poleward-flowing surface waters. While heat lost to the atmosphere promotes the formation of deep water in the THC, net freshwater inputs tend to inhibit this circulation by reducing surface density. In the North Atlantic, poleward-flowing surface waters can become sufficiently dense (resulting from heat loss to the atmosphere) that they sink, and become a key branch of global deep-water circulation and its associated heat transport.

Ocean modeling studies suggest that the strength of the MOC [measured in millions of cubic meters per second, or Sverdrups ($1 \text{ Sv} \equiv 10^6 \text{ m}^3 \text{ s}^{-1}$), and typically estimated as passing through the 1500-m-depth level] could change dramatically because of anthropogenic greenhouse gas emissions (Manabe et al. 1991; Schiller et al. 1997; Stocker and Schmittner 1997; Stouffer and Manabe 1999; Gregory et al. 2005). In these models, the collapse occurs through two main mechanisms: first, a warmer climate results in warmer, less dense surface waters; second, warmer climates generally intensify the hydrological cycle, including increased freshwater input into the North Atlantic (Schmittner and Stocker 1999). The increased input of heat and freshwater into the North Atlantic reduces surface water densities and therefore the deep-water formation rates. The relative

importance of heat and freshwater forcing in driving the MOC changes varies from model to model (Gregory et al. 2005). In addition, not all models show a change in MOC strength in scenarios of global warming (Latif et al. 2000).

Observation-based estimates of the MOC strength are crucial for resolving these differences. These estimates are typically inferred from hydrographic measurements (Broecker 1991; Macdonald and Wunsch 1996; Peacock et al. 2000; Ganachaud and Wunsch 2000; Smethie and Fine 2001) that are sampled sparsely compared to the relevant spatial and temporal variability (Wunsch 1992; Gruber et al. 2000). MOC variability and the uncertainty in observational estimates make detecting a change difficult (Rahmstorf 1999, 2000). There is some evidence that the ocean circulation has changed in the North Atlantic over the last three to four decades (Schlosser et al. 1991; Dickson et al. 2002; Bryden et al. 2005). Whether the reported circulation changes in the North Atlantic are caused by anthropogenic greenhouse gas emissions or are just part of the natural variability is unclear at this time (Rahmstorf 2000). Although it is the THC, and not the wind-driven component of the MOC, that has been predicted to change as a result of anthropogenic climate change, observational estimates of the strength of the overturning circulation do not readily distinguish between thermohaline and wind-driven components. We therefore refer to changes in the MOC rather than in the THC.

3. Methods

The ability of decision makers to account for a potential response of the MOC to anthropogenic climate change depends on the time at which the information becomes available (Keller et al. 2004, 2007b). Here we present a simple method to simulate our ability to detect a trend in the MOC based on observations. We analyze a model scenario in which MOC changes do occur and investigate the following question: how does our ability to learn about the sensitivity of the MOC to forcing depend on observation frequency and observation error? We focus on the example of MOC observations, but the approach could also be applied to other time series.

We account for two key sources of uncertainty: first, a single estimate of the true state of the MOC strength involves considerable observation uncertainty; second, even in the absence of climate forcing, the strength of the MOC is not constant in time but instead exhibits temporal variability. We adopt a Bayesian approach to represent these uncertainties and to explore the temporal evolution of the belief about the state of the

MOC. In the Bayesian approach, a prior belief about the probability of a hypothesis is modified in an objective manner by new information. At any time, one may quantify the belief in a hypothesis H_0 by the probability $P_{\text{prior}}(H_0)$. Then, given an estimate of a property ψ , having some bearing on the hypothesis, we can calculate the likelihood, or the conditional probability $P(\psi|H_0)$, that the value ψ is consistent with the hypothesis H_0 . The new (posterior) belief in the hypothesis $P_{\text{post}}(H_0)$ depends on the initial belief and the conditional probability, according to Bayes theorem,

$$P_{\text{post}}(H_0) = \frac{P(\psi|H_0)P_{\text{prior}}(H_0)}{\sum_i P(\psi|H_i)P_{\text{prior}}(H_i)}, \quad (1)$$

where the denominator is the sum over a set of exhaustive and mutually exclusive hypotheses H_i .

Here we wish to discriminate between two alternative hypotheses. The first hypothesis (H_c) is that the MOC maintains a constant long-term mean overturning strength. We approximate this hypothesis with the model

$$H_c: \psi(t) = \psi_s + \epsilon, \quad (2)$$

where $\psi(t)$ is the MOC strength through time, ψ_s is its mean value in an unforced climate system, and ϵ represents unresolved internal variability. For simplicity, we approximate ϵ as normally and independently distributed with a zero mean and standard deviation of σ [cf. Eq. (7), below]. We will return to the potential effects of this approximation in section 5 (below).

The second hypothesis (H_s) is that the MOC is sensitive and responds to greenhouse gas forcing by declining from its stable climatological strength at some long-term linear rate α . This approximation is expressed in a simple linear model

$$H_s: \psi(t) = \psi_s - \alpha t + \epsilon, \quad (3)$$

where ϵ is defined as in Eq. (2). This linear model is a reasonable approximation over the century time scale of interest in this analysis (cf. Fig. 1, below). We limit this analysis to a simplified description with only two possible MOC models—one in which the MOC decreases at a rate defined by the “fingerprint” of a model in question (discussed below), and one in which it remains stable. This description is, of course, a simplification of the range of possible MOC trajectories, but can be extended easily to more complex settings. In essence, this approach is equivalent to Bayesian model averaging (Hoeting et al. 1999) with two models. The current setup allows us to derive some general insights from a simple and transparent framework. Applying

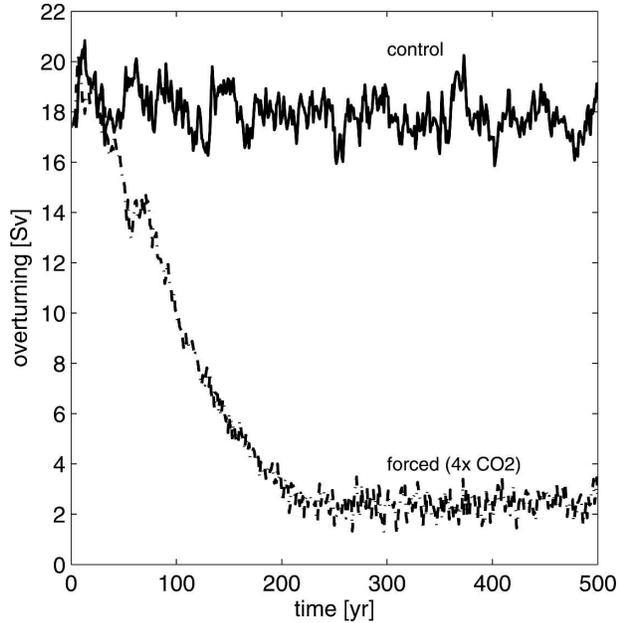


FIG. 1. Comparison of the meridional overturning (a measure of the MOC strength) for control and the forced ($4 \times \text{CO}_2$) scenarios of the GFDL AOGCM (Manabe and Stouffer 1994). The plotted values are the maximum of the meridional streamfunction in the North Atlantic. See Gregory et al. (2005) for an overview of other MOC simulation results.

Bayes' theorem to each hypothesis yields the ratio of the probability of the two hypotheses

$$\frac{P_{\text{post}}(H_c)}{P_{\text{post}}(H_s)} = \frac{P(\psi|H_c)P_{\text{prior}}(H_c)}{P(\psi|H_s)P_{\text{prior}}(H_s)}, \quad (4)$$

which provides a measure of the relative probability of one hypothesis against the alternative given the observations, the priors, and the structural assumptions.

To complete the formulation of the Bayesian updating procedure, we need to specify the likelihood of measuring a value ψ , conditional on a given hypothesis. This likelihood depends on the magnitude of the unresolved internal variability of the MOC strength (σ_s) as well as the uncertainty associated with each individual observation (σ_{obs}) of ψ . We assume, for simplicity, that the effective error is reasonably approximated by independently, identically, and normally distributed errors. In this case, the likelihood of measuring a particular value ψ_i given the hypotheses H_s and H_c is given by

$$P(\psi_i|H_s) \propto \exp \frac{(\psi_i - \psi_c)^2}{2\sigma^2}, \quad \text{and} \quad (5)$$

$$P(\psi_i|H_c) \propto \exp \frac{(\psi_i - \psi_s)^2}{2\sigma^2}, \quad (6)$$

where ψ_s and $\psi_c = \psi_s - \alpha t$ are the expected values of ψ under the respective hypotheses, and σ is the total effective error of a single observation, defined by

$$\sigma^2 = \sigma_{\text{obs}}^2 + \sigma_s^2. \quad (7)$$

Bayes' theorem thus provides a way to modify the belief in a changing MOC after each new measurement. Given the model structure, an initial belief, and a time series of observed overturning strength, this framework allows us to simulate the evolution of the belief in a changing MOC by iteratively applying Eq. (4) after each new observation. Here we are interested in the future development of the belief in an unchanging MOC strength. Because future observations are not available, we adopt a set of simulated values that represents one possible trajectory of the MOC. Using the simulated response of the MOC to anthropogenic CO_2 emissions, we can compute the evolution of the ratio of the probabilities for the alternate hypotheses following each new simulated observation.

Our analysis is limited in scope and based on several approximations. We simply want to assess how quickly one might learn about a changing MOC if one particular model that predicts an MOC collapse turns out to be correct. We will return to a discussion of key caveats after the results and discussion section.

4. Results and discussion

a. Scientific analysis

We now apply this detection method to the response of the MOC in a coupled atmosphere–ocean climate model. The use of a single model is, of course, vulnerable to the effects of structural model uncertainty (Draper 1995; cf. discussion in section 5, below). The results of this detection study depend on the nature of the assumed MOC trajectory. Detecting an MOC change will occur faster for higher signal-to-noise ratios (i.e., the ratio between the MOC changes resulting from anthropogenic forcing and the total effective error). We would like to determine whether a given MOC observation system would enable a detection of MOC changes even under circumstances that are relatively favorable for detection. We therefore choose a model with a relatively high signal-to-noise ratio, that is, a model with a relatively large MOC response and a relatively low internal variability compared to the suite of available models (Cubasch and Meehl 2001; Gregory et al. 2005).

The Geophysical Fluid Dynamics Laboratory (GFDL) coupled ocean–atmosphere model in the setup described in Manabe and Stouffer (1994) is one poten-

tially useful choice in this regard, because it exhibits an MOC collapse that is relatively fast compared to those of other models (Cubasch and Meehl 2001). In addition, the internal variability in the GFDL model is relatively small, compared to other models [e.g., Santer et al. (1995)]. The GFDL coupled ocean–atmosphere model as described in (Manabe and Stouffer 1994) consists of an atmospheric model using the spectral element method with nine vertical levels. This atmospheric model is coupled to an ocean model with a 4.5° latitude and 3.7° longitude resolution, 12 finite difference vertical levels, and isopycnal mixing following (Bryan 1987). The model assumes that ice sheets do not melt. The model is initialized using observed oceanic conditions (Levitus 1982). The “control” scenario is without anthropogenic greenhouse gas forcing. In the forced scenario under consideration, atmospheric CO_2 increases at $1\% \text{ yr}^{-1}$ and stabilizes at 4 times the pre-industrial level ($4 \times \text{CO}_2$). In the control scenario, the modeled MOC has a deep-water formation rate of approximately 18 Sv, with a relatively small interannual variability characterized by a standard deviation of about 1 Sv. In the $4 \times \text{CO}_2$ forced scenario, the MOC reduces to approximately 6 Sv after 150 yr and stabilizes at roughly 3 Sv after approximately 250 yr (Fig. 1). The least squares estimate of the linear MOC slope for the $4 \times \text{CO}_2$ forced scenario is -0.08 Sv yr^{-1} over the first 150 yr. This slope is used as the fingerprint (parameter α) for the hypothesis of a sensitive MOC [Eq. (3)].

We apply the detection method to this model output with a simulated monitoring system representing the observation period and estimation error of recent ocean measurements. The two previous global-scale oceanographic expeditions on which estimates of MOC strength have been based were the Geochemical Ocean Sections Study (GEOSECS) in the 1970s and the World Ocean Circulation Experiment (WOCE) in the 1990s. These expeditions collected very different types of data, and estimates of MOC strength were made with different methods. Nonetheless, we take a 20-yr observation period to represent the status quo for established measurement programs capable of estimating the MOC strength. As discussed in Baehr et al. (2007), hydrographic transects provide a snapshot of the MOC that is “blurred” on time scales from months to years. Hydrographic transects might, hence, provide limited information on variability on shorter time scales. Observation systems based on relatively sparse measurements face additional challenges resulting from potential changes in the spatial structure of the MOC (Wood et al. 1999).

Global inverse calculations of the circulation from

the resulting hydrographic observations typically yield a standard error in the MOC intensity of roughly 2–5 Sv (Broecker 1991; Peacock et al. 2000; Ganachaud and Wunsch 2000; Smethie and Fine 2001). We adopt an observation error of 3 Sv to characterize MOC estimates based on hydrographic observations and perform sensitivity studies with respect to this parameter spanning the range of 1–5 Sv. We illustrate the updating process with an uninformative prior where the two hypotheses are initially (i.e., before the observations are considered) assumed to be equally likely. As can be seen from Eq. (4), the two priors then cancel each other out for the first observation and the resulting likelihood ratio is equivalent to the one derived using a Frequentist approach.

By sampling the model data at 20-yr intervals and superimposing a random observation error (σ_{obs}) of 5 Sv, we can estimate the development of the posterior belief over time (sometimes referred to as a learning curve) in the hypothesis of a stable MOC. Such a learning curve for a single realization of the observation error is illustrated in Fig. 2a. With each observation (denoted by a circle) a previous prior is updated to account for the new information, reflected in the posterior belief (denoted by a square). The posterior belief then becomes the prior for the next iteration at the next observation time. Following Santer et al. (1995), we refer to the time at which 95% certainty is reached as the detection time (represented by the dashed horizontal line in Fig. 2). The detection time in this situation is a random variable, because it depends on random observation errors. For this example, the change in the MOC is initially quite small and the posterior does not change much compared to the initial prior of 0.5. For an observation frequency of every 20 yr and the specific example realization of observation errors of 5 Sv, the detection time exceeds a century (Fig. 2a). For an observation system with an increased observation frequency of every 5 yr and a decreased observation error of 3 Sv (Fig. 2b), detection occurs earlier, within approximately 70 yr.

We now ask whether detection could occur early, that is, before past actions have committed future societies to a threshold response. Addressing this question requires an analysis that accounts for the dynamics of the coupled natural–human system. This is because the timing of the threshold triggering depends on economic factors (e.g., projections of greenhouse gas forcing). This analysis is described in the following section. One key result from this analysis is an estimate of the decision time—the time when a strategy based on a belief of an insensitive MOC starts to differ consider-

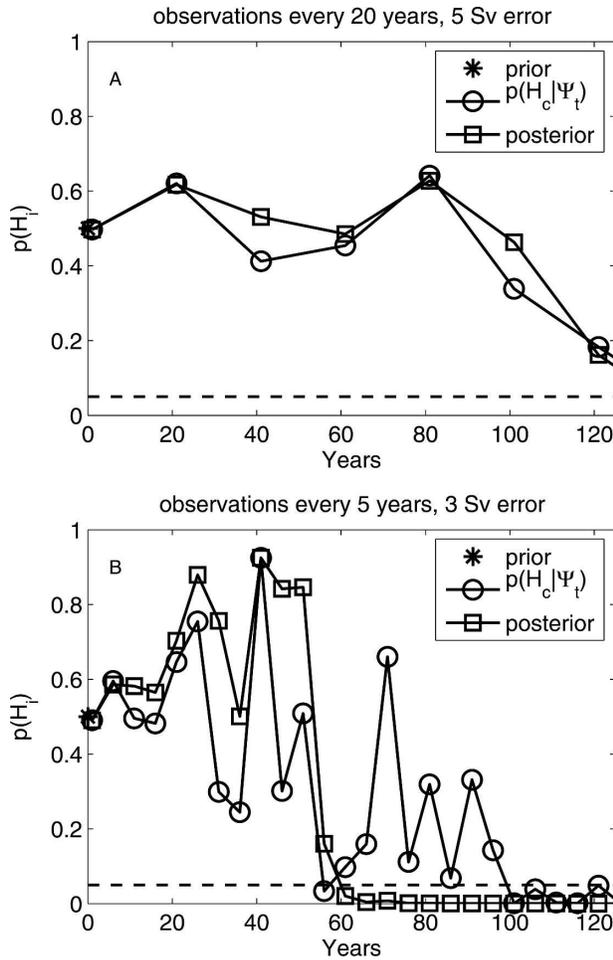


FIG. 2. Development of the belief in a stable MOC (H_c) when the observations are actually derived from the alternative model (H_s). Shown are results for a single draw from the random observation errors. The simulations are for a prior belief in H_c of 0.5. (a) An approximate continuation of the currently implemented MOC observation system is mimicked. (b) A possible improvement based on an increased observation frequency and a decreased observation error is analyzed.

ably from a strategy based on the belief of a sensitive MOC. This decision time is estimated in the simple economic analysis (discussed below) as being approximately 75 yr. Thus, as shown in Fig. 2, an MOC-monitoring program continuing current practice might well fail to detect an MOC change before the decision time. Detecting an MOC change before the decision time is possible, however, through various combinations of observation frequency and observation error. As shown in Fig. 3, the median detection time (based on a Monte Carlo analysis over several realizations of observation errors) decreases with more precise and/or more frequent observations. Hence, detection could be achieved in the considered example before the decision time.

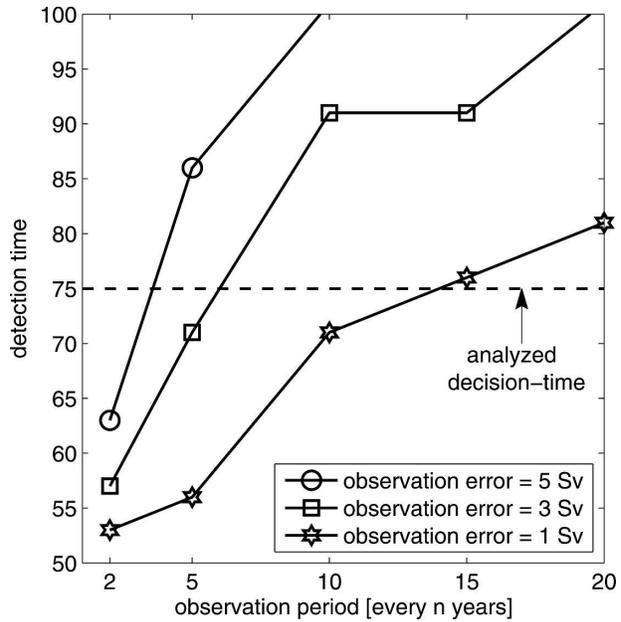


FIG. 3. Sensitivity of the detection time to observation error and observation period. Shown are the median values of the detection time based on 100 Monte Carlo samples.

b. Economic analysis

The implications of a potential MOC collapse on economically efficient climate management have been the subject of numerous analyses (Lempert et al. 1994; Nordhaus 1994; Toth et al. 1998; Keller et al. 2004; McInerney and Keller 2007). The economic damages associated with an MOC collapse are very uncertain, but arguably nonnegligible (Tol 1998; Keller et al. 2000). Avoiding an MOC collapse would imply a considerable increase in greenhouse gas control relative to a strategy neglecting an MOC collapse (Keller et al. 2000; Zickfeld and Bruckner 2003). This implies that significant losses could result from either one of two errors in choosing a strategy: (i) either choosing to invest too little in CO_2 control, and thus failing to prevent an impending MOC collapse; or (ii) choosing to invest too much in CO_2 abatement in order to prevent an MOC collapse that would not have occurred. Either error is costly, so information about the MOC sensitivity has potential economic value. The benefits derived from improved information about an underlying decision problem are referred to as the economic value of information (VOI; Bradford and Kelejian 1977; Manne and Richels 1991).

We examine the economic value of a hypothetical MOC observation system that would deliver a confident and early MOC prediction in the following four steps: (i) we estimate the costs of CO_2 abatement re-

quired to avoid an MOC collapse in a simple economic model, (ii) we derive rough bounds for the economic losses associated with an MOC collapse based on published values, (iii) we approximate the strategy choice as a binary decision problem, and, finally, (iv) we calculate the economic value of information associated with early prediction. We put the magnitude to this economic value of information into perspective by comparing it with order-of-magnitude estimates of the costs of implemented ocean observation systems.

First, we estimate the cost C of preserving the MOC using a model of economically optimal climate management. We adopt the Dynamic Integrated Climate Economy (DICE) model (Nordhaus 1994) as a simple description of the economic trade-offs between consumption and CO_2 abatement. The DICE model couples simple submodels of economically optimal growth (Ramsey 1928), climate change, the related economic damages, and the costs of reducing anthropogenic CO_2 emissions. In the DICE model, abating CO_2 emissions imposes costs but reduces environmental damages. The trade-off between abatement costs and environmental damage is evaluated by the effects on a weighted sum of the consumption of goods by present and future generations. In this framework, an economically optimal strategy of CO_2 control maximizes a weighted sum of the utilities of per capita consumption. The DICE model has been used in a wide variety of economic studies addressing global climate change, and the results are broadly consistent with more complex economic models (Dowlatabadi 1995). The DICE model has the advantage of simplicity and transparency, but has clear limitations (discussed below).

We represent a possible MOC collapse in the DICE model by imposing an additional constraint on the equivalent atmospheric CO_2 concentrations (Keller et al. 2000). Specifically, we require the stabilization of equivalent atmospheric CO_2 concentrations below the critical CO_2 level estimated by Stocker and Schmittner (1997) to preserve the MOC (cf. Fig. 4b). Satisfying the MOC constraint requires a stronger reduction of industrial CO_2 emissions, and hence additional costs, than the optimal strategy without the MOC constraint (Fig. 4c). An optimal economic path in the model, with the additional constraint of MOC preservation, requires additional CO_2 abatement costs with a total net present value of approximately 0.7% of gross world product (GWP). (All GWP numbers are relative to the arbitrary reference year 1995.)

Higher investments into reducing CO_2 emissions (Fig. 4c) result in a smaller increase in atmospheric-equivalent CO_2 concentrations (Fig. 4b) and in a smaller increase in globally averaged surface tempera-

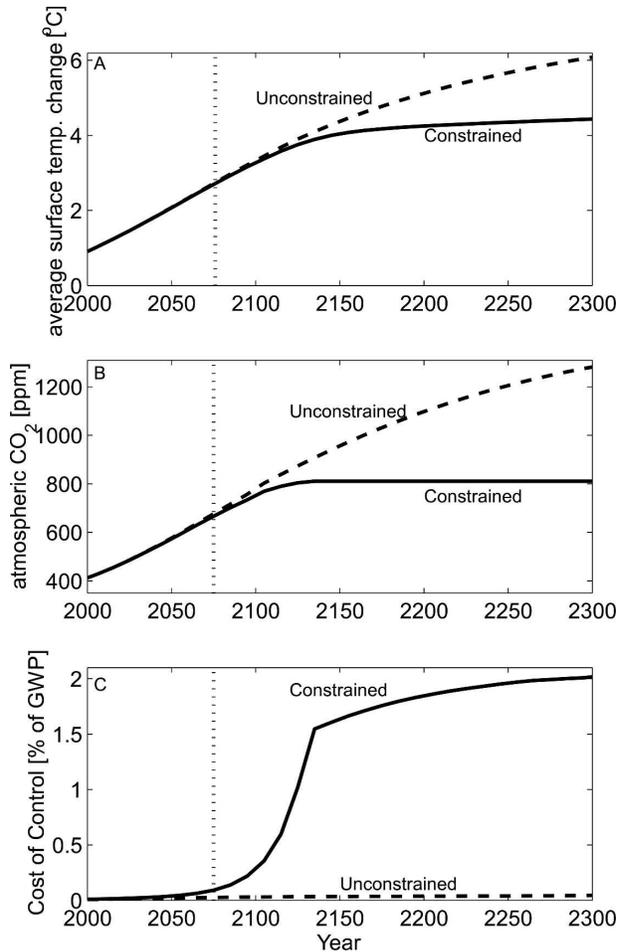


FIG. 4. Estimation of the additional costs of avoiding an MOC collapse. The calculations are based on the DICE-94 model of Nordhaus (1994) with the additional constraint to keep the equivalent CO_2 concentrations below the critical level to preserve the MOC in the model of Stocker and Schmittner (1997). (a) The effects of the (b) reduced atmospheric CO_2 concentrations on globally averaged surface temperatures are shown. (c) The dashed vertical line illustrates the time when the investments in CO_2 abatement start to diverge considerably. This time is the adopted decision point in this specific example.

tures (Fig. 4a). The divergence between the cost paths with and without an MOC preservation constraint is used to estimate the decision time. In the model, the optimal investments in CO_2 abatement with and without an MOC preservation constraint start to diverge considerably around the year 2075 (Fig. 4c), well before the CO_2 concentration in the unconstrained case exceeds the CO_2 threshold (Fig. 4b). The divergence in optimal strategy before the threshold is reached is driven, in part, by nonlinearity in the cost of CO_2 abatement as more and more CO_2 emissions have to be cut back. In the model, smaller relative reductions in CO_2 emissions are more than proportionally cheaper than

TABLE 1. Expense matrix for the simplified decision model applied to an MOC collapse. The net present value of the costs of stabilizing CO₂ below the critical value given by Stocker and Schmittner (1997) and a climate sensitivity of 3.6°C (Tol and de Vos 1998) minus the ancillary benefits of reduced climate damages related to the reduced warming C , which is estimated as 0.7% of GWP in the DICE model of Nordhaus (1994). All GWP numbers are given for the reference year of 1995 and in units of 1989 U.S. dollars. For reference, the 1995 GWP in the DICE model is around 24 trillion U.S. dollars (Nordhaus 1994, p. 83). The net present value of additional damage caused by the MOC collapse is represented by L , which would be 0.9% of GWP if the additional MOC damages cause a stream of 1.5% GWP loss per year after the MOC collapsed using the model of Nordhaus (1994). The decrease in the considerable damages of 1.5% of GWP in the future to a present value of only 0.9% of GWP arises from the application of the monetary discount rate.

Strategy	MOC collapsed	MOC not collapsed
Stabilize CO ₂	Costs = 0.7% of GWP	Costs = 0.7% of GWP
Do not stabilize CO ₂	Losses = 0.9% of GWP	Base case

larger relative reductions. This is because an economically efficient strategy uses the cheapest option before it moves on to add more expensive options. One effect of the increasing marginal abatement costs is that delaying a large CO₂ abatement can increase the net present value of the costs (imposing the same atmospheric CO₂ constraint). Thus, an economically optimal strategy to preserve the MOC in this framework requires taking action well before the physical threshold (represented by the CO₂ level below which the constrained strategy stabilizes, cf. Fig. 4b) is reached.

Second, we derive a rough order of magnitude estimate of the economic damages L resulting from an MOC collapse by reviewing previous studies. This problem is an area of active research, and the results so far are deeply uncertain. Previous studies suggest that MOC collapse might cause considerable economic damages (Tol 1998; Keller et al. 2000). According to Tol's (1998) estimate, a thermohaline circulation collapse may temporarily increase the climate damage by up to 3% of gross domestic product in western Europe. Keller et al. (2000), for example, discuss the economic impacts of decreased oceanic CO₂ uptake, decreased fishery yields, and changes in atmospheric surface temperature, and estimate the order of magnitude for a subset of MOC-specific damages between 0% and 3% of the GWP. Here we adopt a uniform probability distribution over this range with a mean of 1.5% of GWP per year. (It is important to note that the current estimates of MOC-specific economic impacts are incomplete. Adopting higher estimates of the MOC-specific economic impacts would result in higher economic values of information and would strengthen our forthcoming conclusions.) We impose this additional damage in the economic model whenever the equivalent CO₂ exceeds the critical CO₂ level. The resulting expected net present value of MOC specific losses L is equivalent to approximately 0.9% of GWP (Table 1).

Third, we analyze a specific decision-making problem characterized by a binary decision at a single decision point in time. In this case, we can characterize the

decision problem by a 2×2 decision matrix that summarizes the possible outcomes and their costs and probabilities (Katz and Murphy 1997). For the analyzed problem, the decision matrix consists of the following two possible future MOC states: (a) an MOC collapse or (b) no MOC collapse. These MOC states are combined with two available decisions: (i) to preserve or (ii) not to preserve the MOC. The task of the decision maker in this stylized problem is then to choose the strategy that maximizes the net expected benefit among all of the possible outcomes in the decision matrix. This optimal strategy minimizes the overall expected costs of climate change and climate control, where the expected net cost for either strategy is the sum of the costs and losses weighted by the probability that the corresponding MOC state occurs. Of course, many other decision-making frameworks and rules are possible (e.g., Kahneman and Tversky 1979; Lempert and Schlesinger 2000; or McInerney and Keller 2007), which would likely result in different outcomes.

Given this strategy, we can draw a number of conclusions from the estimated costs and losses shown in Table 1. First, for an impossible MOC collapse ($p = 0$), this stylized decision maker faced with this simplified problem would not choose the preservation strategy, because the additional costs of maintaining atmospheric CO₂ below the threshold value would exceed the zero losses. For a certain MOC collapse (given a no-stabilization strategy) ($p = 1$), the optimal strategy would be to stabilize CO₂, because the losses L resulting from an MOC collapse exceed the costs of the preservation strategy. Thus, the optimal strategy under the risk of an MOC collapse depends strongly on the belief in the likelihood of such a collapse.

A risk-neutral decision maker maximizing the net benefit in this simplified problem would choose the strategy that minimizes expected costs ($\min [C, p \cdot L]$). Thus, for $p > (C/L)$ (where (C/L) is the cost-loss ratio), the optimal decision is to invest in climate control to reduce the risk of an MOC collapse. For $p < (C/L)$ the optimal decision in this framework would be to choose

the strategy of not stabilizing the CO₂, and thus taking the risk of an MOC collapse. (Whether such a risk-taking strategy is a reasonable description of the behavior of the real decision-making process is an open question.) The optimal strategy in this stylized problem changes from the choice of risking an MOC collapse to the choice of avoiding an MOC collapse as the probability of an MOC collapse rises above the cost–loss ratio, or roughly 80%.

Fourth, we identify the effect of obtaining additional information about the MOC on the expected costs of both considered strategies. Ocean observations can be used to revise the probabilities upon which the decision maker acts. Because information about the true state of the MOC is expected to reduce the likelihood of the costly strategy errors discussed above, ocean-monitoring programs can have economic value. The value of information obtained through a monitoring program depends on the quality of that information.

Following Katz and Murphy (1997), we define the quality of information obtained through monitoring as

$$q = \frac{P - P_o}{1 - P_o}, \quad (8)$$

where P is the probability of an MOC collapse at the decision point [equal to $P_{\text{post}}(H_s)$], and P_o is the initial belief before monitoring begins. This definition of quality measures the change in the belief in an MOC collapse as a result of monitoring. A monitoring system that leaves our prior belief unchanged ($P = P_o$) has zero quality, whereas one that achieves certainty has $q = 1$.

The VOI can be computed as the decrease in expected net present value of the costs that results from learning about the probability of MOC collapse. It is obtained by subtracting the expected costs incurred by a policy with information from the expected costs incurred by a policy operating from prior belief only. The VOI is related to the quality of information, or equivalently to the level of belief that can be obtained by the decision point. As derived by Katz and Murphy (1997), the value of information for the case of $(C/L) < P < 1$ is

$$\text{VOI}(q) = P_o \{ [P_o + (1 - P_o)q]L - C \}. \quad (9)$$

This expression satisfies the intuitive expectation that monitoring schemes that achieve greater certainty (and therefore have higher quality) have more value than those that leave the initial uncertainty unchanged. For the considered costs, losses and prior, an observation system that would deliver a relatively confident prediction (e.g., a quality of 0.9) would have an economic value of information on the order of 0.1% of GWP, a

number in the tens of billions of U.S. dollars. It is important to note that this value of information is associated with a confident and early *prediction* of MOC changes. In contrast, our scientific analysis considers the question of MOC change *detection*. (As a technical point, detection and prediction are equivalent in the simplified example analyzed in this study. This is, however, not the case once a more realistic representation of the relevant structural and parametric uncertainties is considered.)

One might ask whether investment in an MOC observation system would pass an economic cost–benefit test. The economic value of information associated with an MOC observation system that would deliver an early and confident prediction is on the order of tens of billions of U.S. dollars. Currently implemented MOC observation systems have net present value costs on the order of tens of millions of U.S. dollars over an implementation time scale of decades (Baehr et al. 2007). Identifying the design of a feasible MOC observation system that would deliver an early and confident prediction across the relevant range of parametric and structural uncertainties is, at this time, an open challenge (Keller et al. 2007b). Such an MOC observation system, implemented at costs below the estimated value of tens of billions U.S. dollars would pass an economic–benefit test.

5. Caveats and open questions

Our conceptual study should be interpreted as a first step toward the economic analysis of a possible MOC observation system and is adorned with numerous caveats. Here we briefly outline a subset of potentially important refinements.

First, this study analyses a single ocean model, similar to previous analyses of ocean observation systems (Köhl and Stammer 2004; Baehr et al. 2004, 2007). While understanding the detection problem for a single model is a logical first step, our analysis is silent on the effects of model uncertainty (Gregory et al. 2005), considering a larger number of ensemble runs (Baehr et al. 2007), or systematic observation errors (Baehr et al. 2007). It may well be that considering these effects would result in more stringent requirements (i.e., higher observation frequency and lower observation error) for the observation system to result in early detection.

The studies by Baehr et al. (2007) and Keller et al. (2007a) may provide some relevant information regarding the robustness of the detection results with respect to structural uncertainty and methodological assumptions. Baehr et al. (2007) use a different atmosphere–

ocean general circulation model (AOGCM) [ECHAM5/Max Planck Institute Ocean Model (MPI-OM)] driven by a more realistic radiative forcing than the current study to analyze the detection time using virtual observations at 26°N. They also use a different detection method based on a Frequentist approach and account for the effects of potential autocorrelation of the MOC time series. Baehr et al. (2007) derive median detection times for annual observations and an observation error of 3 Sv around 50 yr. This is broadly consistent with our estimate of a median detection time of approximately 60 yr for observations every 2 yr and an observation error of 3 Sv. Keller et al. (2007a) use the same detection method as that of Baehr et al. (2007) and apply it to the model simulations of Manabe and Stouffer (1994). They find that annual observations with an observation error of 3 Sv result in a median detection time of approximately 50 yr. Thus, our conclusion that more frequent MOC observations with lower observation errors can result in early MOC change detection seems to be somewhat robust with respect to choosing an alternative statistical method, a different AOGCM, and a more realistic forcing. Of course, a sample of just two AOGCMs and two detection methods covers only a small subset of the relevant uncertainties. A more robust assessment of the detection capabilities of a given MOC observation system would be required to analyze the performance of this system across a sufficiently large sample of structural and parametric uncertainty.

Second, we neglect the effects of potential temporal autocorrelation in unresolved MOC variability [σ_s term in Eq. (7)]. Accounting for autocorrelation increases the uncertainty in the estimated slope (Zellner and Tian 1964). The effects of autocorrelated errors in σ_s on the likelihood functions [Eqs. (5) and (6)] are, however, reduced by the considerable observation error [σ_{obs} term in Eq. (7)] that is assumed to be independently distributed. As discussed above, the results of Baehr et al. (2007) and Keller et al. (2007a) suggest that accounting for the effects of temporal autocorrelation in the unresolved MOC variability (in addition to other model refinements) does not change the main conclusion of our detection study.

Third, the future detection time is a stochastic variable and we analyze so far only the medium value. This poses the question of how different levels of reliability affect the design of the observation system as well as the economic analysis (Baehr et al. 2007; McInerney and Keller 2007). Addressing these questions will require a more refined characterization of the decision-making problem than the one adopted in this study.

Fourth, it is important to note that the adopted economic model contains a large number of approxima-

tions and value judgments that affect the conclusions. Key issues that would likely benefit from a more refined treatment include the descriptions of (i) temporal discounting (Bradford 1999; Newell and Pizer 2003), (ii) the decision criterion (Lempert 2002; McInerney and Keller 2007), (iii) technological inertia (Grubler 1991; Wigley et al. 1996), (iv) the costs of reducing greenhouse gas emissions (Keller et al. 2003; Buonanno et al. 2003), (v) the continuous nature of the observation and abatement decisions, and (vi) parametric uncertainties (Tol 2005; McInerney and Keller 2007). Consider, as an example, the effect of the (so far neglected) uncertainty about the climate sensitivity. An analysis based on a higher estimate of the climate sensitivity would result in lower critical CO₂ concentrations (Stocker and Schmittner 1997) and potentially change the decision time (Fig. 4).

Fifth, our scientific analysis is silent on the question of MOC prediction across the relevant range of structural and parametric uncertainties. An accurate MOC prediction with an increased range of MOC responses can impose more stringent requirements on an observation system compared to MOC change detection (Keller and McInerney 2006, manuscript submitted to *Climate Dyn.*). Note, however, that we use just a subset of the available observational constraints and neglect potentially important statistical refinements. Using spatial or spectral fingerprints (Hasselmann 1998; Banks and Wood 2002; Held and Kleinen 2004; Kleinen et al. 2003) and continuous observations (Hirschi et al. 2003), and analyzing additional tracers affected by ocean circulation changes (Keller et al. 2002; Joos et al. 1996; Matear et al. 2000) may well lead to an earlier detection and/or prediction of potential MOC changes.

6. Conclusions

We analyze when an MOC observation system would detect anthropogenic MOC changes. Specifically, we adopt a Bayesian statistical framework to estimate the time required to detect the weakening MOC signal in a specific model simulation. We conclude that decadal-scale hydrographic observation system may well fail at early detection (i.e., detecting anthropogenic MOC changes before the system is committed to an MOC threshold response). Increasing the observation frequency and/or precision can result in early detection. We estimate the economic value of information associated with a hypothetical MOC observation system that would enable an early and confident MOC prediction. Our analysis suggests that the economic value of such an MOC observation system can exceed the costs of currently implemented observation systems by orders

of magnitudes. One key outstanding challenge is to identify a design of an MOC observation system that could provide a reliable early prediction of a potential MOC threshold response across the range of parametric and structural uncertainties.

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This paper is dedicated to the memory of David F. Bradford.

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