

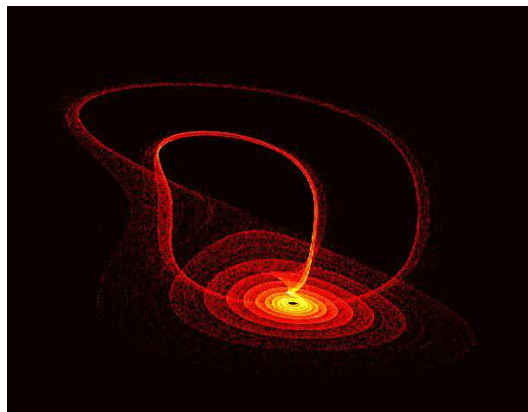
**HABILITATION À DIRIGER DES RECHERCHES
UNIVERSITÉ DE BRETAGNE OCCIDENTALE**

Spécialité :
Physique de l'Océan et Dynamique du Climat

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**Interannual to Decadal Predictability of the
North Atlantic**

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Details Matter



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Remerciements

I would like to gratefully thank all my collaborators that have helped me shape this research over the years from France to US, UK, and Holland.

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Résumé

La circulation méridienne de l'Atlantique (AMOC) est une circulation océanique à l'échelle du bassin Atlantique. Son transport de chaleur vers le nord contribue à l'équilibre climatique de la planète. Cette circulation peut être schématiquement décrite comme un transport d'eau chaude vers le nord en surface compensé par un transport d'eau froide vers le sud en profondeur. La capacité thermique d'une couche de 2 m d'eau de mer est équivalente à celle de l'atmosphère dans son entier, ainsi le contenu de chaleur océanique domine le réservoir énergétique de la Terre. Grâce à cela et à ses variations lentes, l'AMOC régule le climat de l'Atlantique nord et contribue au climat tempéré de l'Europe. Ainsi, prévoir les variations de l'AMOC est crucial pour prévoir les variations climatiques des régions bordant l'Atlantique nord. De façon similaire à la prévision météorologique, les prévisions climatiques sont basées sur des simulations numériques de l'état du climat. Néanmoins, prévoir de manière correcte sur des échelles aussi longues est loin d'être évident. Même sous l'approche modèle-parfait, où les biais entre les modèles et la réalité sont ignorés, la nature chaotique de la variabilité de l'AMOC (c'est-à-dire sa sensibilité à la condition initiale) est une source significative d'incertitude, limitant la précision des prédictions.

Les études de prévisibilité s'intéressent aux facteurs déterminant notre capacité prédictive plutôt que de faire des prévisions. Ainsi, les mécanismes affectant la prévisibilité de l'AMOC peuvent être séparés en deux catégories : les processus agissant comme source de prévisibilité (oscillations harmoniques périodiques) et les processus agissant comme source d'incertitude (la croissance d'erreur qui modifie significativement le résultat de simulations numériques). Pour comprendre la première catégorie, les modes harmoniques de variabilité ou les précurseurs des variations de l'AMOC sont identifiés. Pour la deuxième catégorie, et sous l'approximation modèle-parfait, les sources d'incertitude sont caractérisées par la dispersion des simulations numériques différenciées par une erreur sur leur condition initiale. Deux cadres d'étude alternatives et complémentaires sont apparus pour étudier cette dispersion. Le cadre d'étude pragmatique correspond à faire des simulations d'ensemble, en imposant une petite erreur aléatoire à la condition initiale des simulations individuelles. Ceci permet une approche probabiliste et de caractériser statistiquement l'importance de la condition initiale en évaluant la divergence de l'ensemble. Le cadre d'étude théorique s'intéresse aux études de stabilité pour identifier les petites perturbations sur la condition initiale qui induisent un changement significatif de l'AMOC.

En parallèle de ces études fondamentales sur la prévisibilité, les systèmes de prévisions décennales ont été développés et testés à travers une large gamme de prévisions à rebours. Les difficultés inhérentes aux systèmes opérationnels de prévisions vont du développement de méthodes efficaces d'initialisation à fixer les forçages radiatifs, en passant par la correction des biais et des dérives des modèles numériques. Toutes ces améliorations sont testées et validées grâce à une gamme de mesures spécifiquement développées pour cela.

Abstract

The Atlantic Meridional Overturning Circulation (AMOC) is a large, basin scale circulation located in the Atlantic Ocean which transports climatically important quantities of heat northward. It can be described schematically as a northward flow in the warm upper ocean and a southward return flow at depth in much colder water. The heat capacity of a layer of 2 m of seawater is equivalent to that of the entire atmosphere therefore ocean heat content dominates Earth's energy storage. Because of this and the AMOC's typical slow decadal variations, the AMOC regulates North Atlantic climate and contributes to the relatively mild climate of Europe. Hence predicting AMOC variations is crucial for predicting climate variations in regions bordering the North Atlantic. Similar to weather predictions, climate predictions are based on numerical simulations of the climate system. However providing accurate predictions on such long timescales is far from straightforward. Even in a perfect model approach, where biases between numerical models and reality are ignored, the chaotic nature of AMOC variability (i.e., high sensitivity to initial conditions) is a significant source of uncertainty, limiting its accurate prediction.

Predictability studies focus on factors determining our ability to predict the AMOC rather than actual predictions. To this end, processes affecting AMOC predictability can be separated into two categories: processes acting as a source of predictability (periodic harmonic oscillations, for instance) and processes acting as a source of uncertainty (small errors that grow and significantly modify the outcome of numerical simulations). To understand the former category, harmonic modes of variability or precursors of AMOC variations are identified. On the other hand, in a perfect model approach, the sources of uncertainty are characterized by the spread of numerical simulations differentiated by the application of small differences to their initial conditions. Two alternative and complementary frameworks have arisen to investigate this spread. The pragmatic framework corresponds to performing an ensemble of simulations, by imposing a randomly chosen small error on the initial conditions of individual simulations. This allows a probabilistic approach and to statistically characterize the importance of the initial condition by evaluating the spread of the ensemble. The theoretical framework uses stability analysis to identify small perturbations to the initial conditions, which are conducive to significant disruption of the AMOC.

Beyond these difficulties in assessing the predictability, decadal prediction systems have been developed and tested through a range of hindcasts. The inherent difficulties of operational forecasts span from developing efficient initialization methods to setting accurate radiative forcing to correcting for model drift and bias, all these improvements being estimated and validated through a range of specifically designed skill metrics.

Chapter 1

Scientific Context

This work was done in collaboration with B. Sinha.

1.1 Introduction

In the context of the current global warming, there is a growing societal demand to predict changes on interannual to decadal timescales to inform mitigation and adaptation strategy (IPCC, 2013). Whereas on multidecadal timescales the long secular warming trend dominates the global average Surface Atmospheric Temperature (SAT), on interannual to decadal timescales “internal” or “intrinsic” variability, generated from the internal dynamics of the climate system rather than external forcing, is the most important factor (more than 80% of the total variance for 10-yr timescales, Fig. 1.1 left). This result has also been suggested by Hawkins and Sutton (2009b) and Meehl et al. (2009), for instance and implies that an accurate prediction of climate changes on interannual to decadal timescales is not strongly dependent on CO₂ emission scenarios, and one needs to concentrate on “natural”¹ variability of the climate system.

Focusing on “internal” variability on decadal and longer timescales, the surface temperature shows an intensified level of variability in the North Atlantic, and in particular in the Nordic Seas (Fig. 1.1 right). This signature is typical of changes in the Atlantic Meridional Overturning Circulation (AMOC) on decadal timescales (e.g., Vellinga and Wood, 2002; Drijfhout, 2015). Also, AMOC changes have been shown to lead to, or at least to be concomitant with, cooling of the North Atlantic ocean surface (Drijfhout et al., 2012; Rahmstorf et al., 2015). So predicting AMOC variations is of first order importance for predicting the North Atlantic surface temperature.

From a physical oceanographic perspective, the AMOC is a basin scale ocean circulation transporting heat polewards in the North Atlantic (Stommel, 1958; Gordon, 1986). This

¹Here we use “natural” and “internal” in a loose sense. Indeed, in a climate that is forced to change by unsteady anthropogenic CO₂ emission, the variations around the long secular trend cannot be strictly considered as “natural”. I.e., the “natural” variability would be the variability of the system at statistical equilibrium. Similarly “natural” variability encompasses both an “internal” part as well as a part caused by non-anthropogenic external forcing such as volcanic eruptions or solar radiation changes.

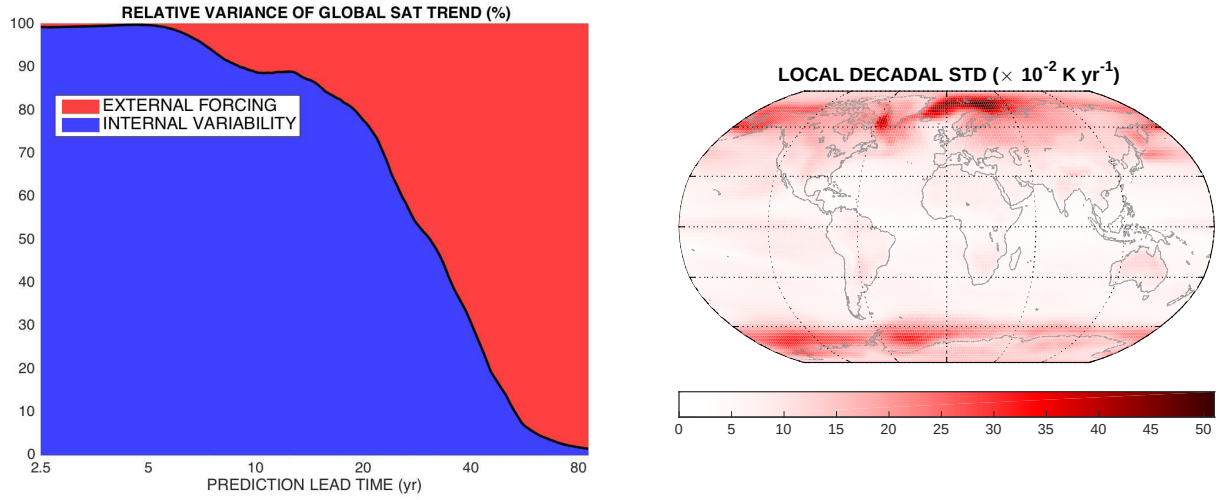


Figure 1.1: (Left) Relative contribution to the total variance of (red) external forcing and (blue) internal variability for the globally averaged Surface Atmospheric Temperature trend. The external forcing is assessed through the variance of multi-model means across 4 RCP scenarios from CMIP5 (RCPs 2.6, 4.5, 6.0, and 8.5) at different lead times. The internal variability is assessed through the variance of the multi-model mean distribution filtered at different timescales, from CMIP5 pre-industrial control simulations. (Right) Multi-model mean of local standard deviation of SAT decadal trend from CMIP5 pre-industrial control simulations.

heat transport is achieved through a northward flow of relatively warm water in the upper $\sim 1,000$ m and a southward flow of relatively cold water at depth. During its poleward journey the surface water exchanges heat with the atmosphere, cooling the surface ocean and warming the surface atmosphere. This warming influences the climate of the North Atlantic and bordering regions, through changes in tropical cyclone activity (Goldenberg et al., 2001), storminess over Europe (Jackson et al., 2015), precipitation over America (Enfield et al., 2001), and African Sahel rainfall (Knight et al., 2006), for instance.

The AMOC has been monitored at 26°N since 2004 (McCarthy et al., 2012; Srokosz et al., 2012; Srokosz and Bryden, 2015). Interannual changes in the AMOC have been suggested to explain the severe winter conditions over northwestern Europe in 2010-2011 and the high intensity hurricane season in summer 2010 (Bryden et al., 2014). These observational results are consistent with state-of-the-art climate modelling studies that have demonstrated AMOC influences on surface atmospheric pressure, surface atmospheric temperature or rainfall patterns on much longer timescales (Sutton and Hodson, 2003, 2005; Knight et al., 2005; Msadek and Frankignoul, 2009).

Hence, beyond the successful monitoring of the AMOC, predicting AMOC changes is essential to predict climate changes on decadal timescales. However, as with many complex systems, AMOC variations are neither regular nor characterised by a well defined period, so predicting its future evolution is far from straightforward. Indeed its evolution is typical of chaotic systems (Strogatz, 1994) meaning that the evolution of the AMOC is highly sensitive to its initial state, and a small error in specifying the initial state might have a significant effect in its predicted future evolution². Hence, it is of the utmost importance to determine AMOC predictability (i.e., the fundamental limits on our ability to predict it), as an essential precursor to, and theoretical underpinning of, actual prediction systems. To further define the difference between predictability studies and actual prediction we can make the analogy with mathematics: predictability is to prediction as the existence of a solution is to the solution in mathematical problems.

In this paper, we will use two conceptual models to illustrate the limits of prediction under stochastic and deterministic chaos. In the context of the AMOC, these two types of chaos represent the synoptic chaotic atmospheric variability forcing the ocean at its surface and the internal chaotic variability, respectively. In the real world both are active and may feedback on each other. Beyond considering these conceptual approaches, we will also describe the state-of-the-art knowledge of AMOC predictability, by describing both contributing and limiting factors. In a more applied framework, we will discuss existing prediction systems for interannual to decadal timescales and their current limits.

In this paper we will ignore a few factors that have an impact on the variability, and hence on the predictability, of the AMOC. For example, we will not discuss the effects of the solar cycles that are highly predictable and pace the climate system. On the other hand, the effect of volcanic eruptions or solar eruptions will also be ignored, even though they are potentially important to set up the AMOC variability (e.g., Swingedouw et al., 2015). In the same way, changes in the geographical location and strength of

²This idea has been popularized by the idiom of the butterfly effect in the context of the atmospheric circulation (Lorenz, 1963).

anthropogenic aerosol sources will not be covered. These effects are unpredictable from a natural science point of view (either due to their random nature or because they are linked to socio-economical changes), and will be assumed to be specified as part of future scenarios. However, these effects will be fully acknowledged and discussed when describing state-of-the-art prediction systems.

The structure of the paper is as follows. In section 1.2 two conceptual perspectives of AMOC predictability are developed. In section 1.3, studies on predictability of the AMOC on decadal timescales are discussed. Description of state-of-the-art prediction systems are given in section 1.4. Finally, section 1.5 includes a short discussion and directions for future work.

1.2 Conceptual perspectives

In this first part, we will use two idealized models to illustrate the conceptual principles of predictability studies. These two models follow two different frameworks used to study and understand the growth of small disturbances (i.e., chaotic behavior). In the stochastic framework, the noise set as external forcing gives rise to divergence between model simulations. In the deterministic framework, it is nonlinearities of the system dynamics that lead to divergence. Hence these two frameworks schematically represent the two sources of uncertainty: external and internal, respectively.

1.2.1 Stochastic framework

The first model will describe the evolution of anomalous Sea Surface Temperature (SST) when subjected to stochastic forcing representing the intrinsic chaotic synoptic dynamics of the atmosphere. Hence the ocean model will be forced by an ensemble of randomly selected anomalous surface atmospheric temperature conditions. This model and framework is equivalent to the studies of Hasselmann (1976) and Frankignoul and Hasselmann (1977) in the context of ocean variability, and Chang et al. (2004) in the context of predictability. The model reads

$$\partial_t \text{SST}_i = (\text{SAT}_i - \text{SST}_i) / \tau, \quad (1.1)$$

where SST_i is the i^{th} realization of anomalous Sea Surface Temperature (top Fig 1.2), SAT_i – the i^{th} realization of anomalous Surface Atmospheric Temperature and τ – an oceanic adjustment timescale (set to 10 yr in numerical applications). We will assume that the SAT follows a white noise distribution ($\langle \text{SAT}_i \text{SAT}_j \rangle = \sigma_0^2 \delta_{i,j}$, where $\delta_{i,j}$ is the Kronecker delta and σ_0^2 – the SAT standard deviation is set to 0.3 K in numerical applications, and angled brackets denote a time average).

This idealized model of a Langevin equation has a solution of the form of an Ornstein-Uhlenbeck process (see for example section 3.4 in Dijkstra, 2013). Thus we can obtain the oceanic variance (σ^2 , middle Fig 1.2) as

$$\sigma^2(t) = \sigma_\infty^2 (1 - e^{-2t/\tau}), \quad (1.2)$$

where σ_∞^2 is the asymptotic oceanic variance. Hence, using a Taylor expansion, we find the useful property that, on short timescales ($t \ll \tau$), the variance grows linearly with time and is fully independent of the system dynamics:

$$\sigma^2(t) \propto t, \text{ for } t/\tau \ll 1, \quad (1.3)$$

This result can be generalized to any linear system, as shown by Chang et al. (2004) consistently with Hasselmann (1976).

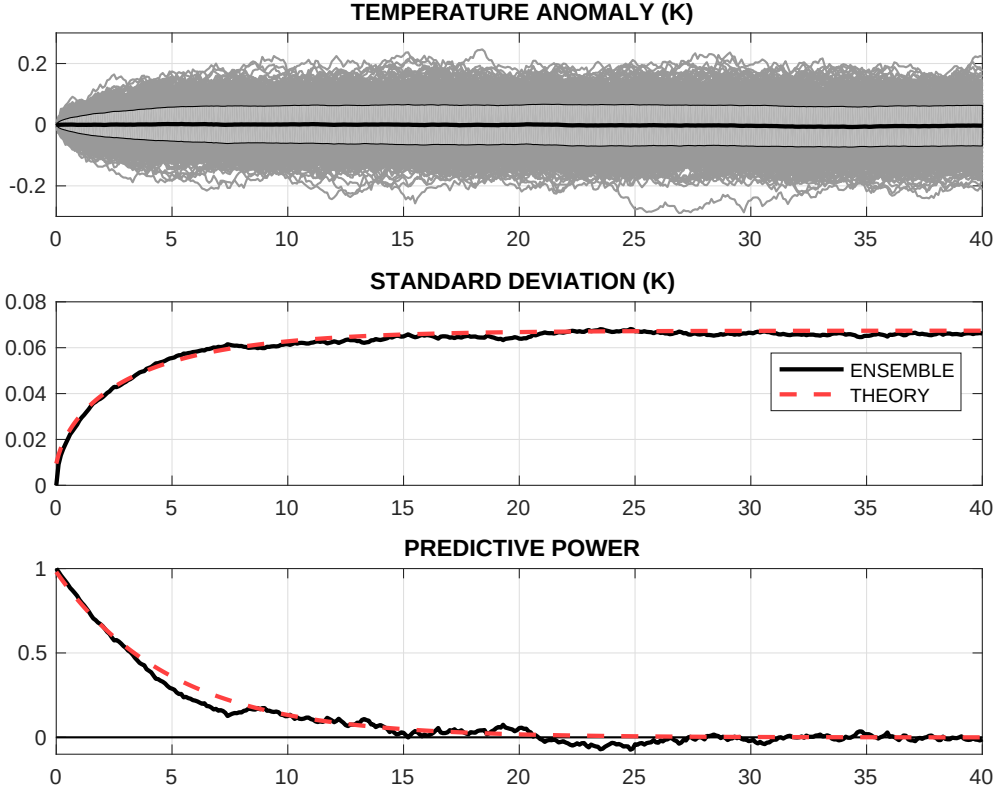


Figure 1.2: (From top to bottom) Sea Surface Temperature anomaly, standard deviation and Predictive Power for the ensemble of 1,000 members (i.e., 1,000 different stochastic realisations) of the idealized stochastic model. The ensemble results (black solid lines) converge toward the theoretical results (red dashed lines) with increasing ensemble size (i.e., numbers of members/realizations, cf. Fig. 1.5).

Following Schneider and Griffies (1999), we define the Predictive Power (PP, bottom Fig 1.2), bounded between 0 and 1, which reads:

$$PP(t) = 1 - \sigma^2(t)/\sigma_\infty^2 = e^{-2t/\tau}. \quad (1.4)$$

This suggests that the predictability of this idealized model in a stochastic framework is solely set by the typical damping rate, τ , of the ocean adjustment. Chang et al. (2004) have demonstrated that this result is unchanged by the presence of oscillatory behavior or non-normality (despite the increase of the variance in the latter case, Ioannou, 1995).

1.2.2 Deterministic framework

In this framework we will use a different model to the previous section. In this new model the chaotic dynamics will be generated internally by nonlinearities of the system. This model is a modification of the Howard-Malkus loop (Welander, 1957, 1965, 1967; Howard, 1971; Malkus, 1972), analogous to the waterwheel model (Strogatz, 1994; Dewar and Huang, 1995, 1996; Huang and Dewar, 1996), and representing AMOC dynamics (Sévellec and Fedorov, 2014, 2015b). This model reads

$$d_t \omega = -\lambda \omega - \epsilon \beta S_{NS}, \quad (1.5a)$$

$$d_t S_{BT} = (\Omega_0 + \omega) S_{NS} - K S_{BT} + \frac{F_0 S_0}{h}, \quad (1.5b)$$

$$d_t S_{NS} = -(\Omega_0 + \omega) S_{BT} - K S_{NS}. \quad (1.5c)$$

The three model variables are the varying component of the ocean meridional overturning (ω) and the vertical (Bottom-Top) and meridional (North-South) salinity gradients (S_{BT} and S_{NS} , respectively), each depending on time (t). Here the circulation is the sum of a steady component of the circulation (Ω_0), set by the mean oceanic temperature gradients and surface winds, and a variable part (ω) controlled by variations in salinity gradients. The model parameters are defined as follows: ϵ is a coefficient setting the rate of change of ocean overturning induced by the buoyancy torque; λ – a linear friction coefficient; β – the haline contraction coefficient; K – a linear damping coefficient; F_0 – the freshwater flux intensity; S_0 – a reference salinity; and h – the loop depth or thickness. Numerical values are given in Tab. 1.1. Hence, the first equation describes the momentum balance, whereas the two other equations describe the evolution of the salinity gradients driven by advection, linear damping and the surface salt flux. For further details about the model we refer the reader to Sévellec and Fedorov (2014, 2015b).

Table 1.1: Parameters of the loop model.

h	1000 m	depth of the level of no-motion (i.e., the loop thickness)
Ω_0	$-2.5 \times 10^{-2} \text{ yr}^{-1}$	thermally- and wind-driven circulation component
F_0	1 m yr^{-1}	freshwater flux intensity
S_0	35 psu	reference salinity
λ	10^{-2} yr^{-1}	friction coefficient
ϵ	0.35 yr^{-2}	buoyancy torque coefficient
K	10^{-4} yr^{-1}	Laplacian eddy diffusion coefficient
β	$7 \times 10^{-4} \text{ psu}^{-1}$	haline contraction coefficient

To study the evolution of this idealized model we set up a large ensemble of 500 members slightly differing by their initial conditions following a multivariate normal distribution of standard deviation of 0.1 psu and 10^{-3} yr^{-1} for salinity gradients and overturning

intensity, respectively. The evolution of the ensemble shows an overall divergence of the trajectories of the 500 members, typical of chaotic systems (Fig. 1.3 left). However, unlike the linear stochastic model, the evolution of the inter-member standard deviation is not monotonic.

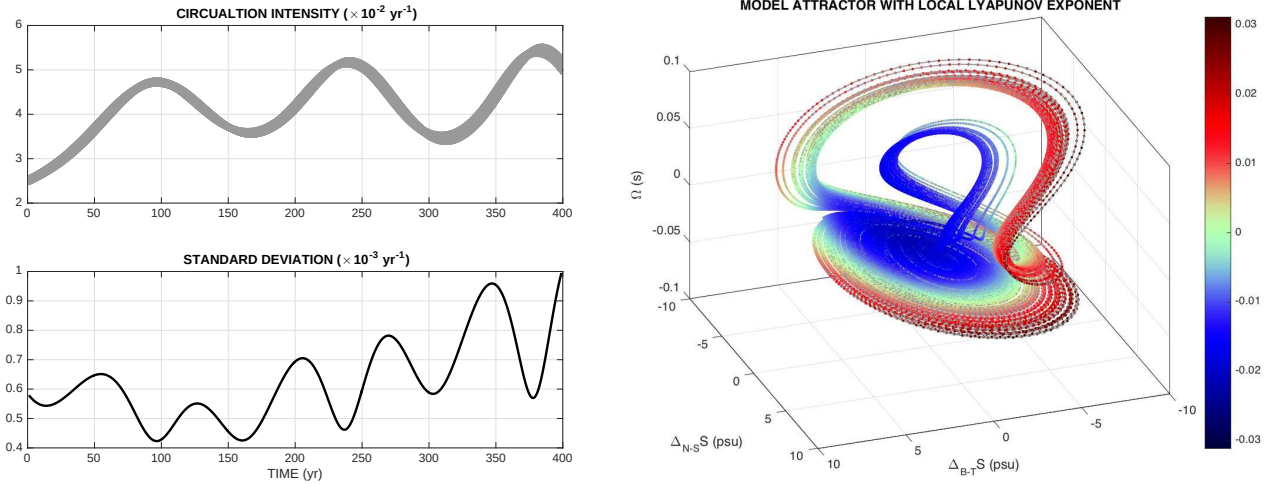


Figure 1.3: (Left from top to bottom) Circulation intensity and standard deviation of the ensemble of 500 members for the deterministic idealized model. (Right) 1 yr local Lyapunov exponent evaluated over the trajectory of the deterministic idealized model, following (1.6). Color represents the growth of the small disturbances (i.e., positive and negative values suggest divergence and convergence of trajectory in phase space, respectively).

The non-monotonic change in the inter-member variance can be characterized by looking at the local Lyapunov exponent (g) computed along the strange attractor of the loop model. For this purpose we compute the 1-year linear growth of normalized perturbations (i.e., the local Lyapunov exponent) along a long trajectory of the loop model covering a large part of the system strange attractor.

$$g(t) = \log [n(t+s)/n(t)]/s, \text{ with } n(t) = \omega'^2(t) + \left(\frac{\epsilon\beta}{\lambda}\right)^2 [S_{BT}'^2(t) + S_{NS}'^2(t)], \quad (1.6)$$

and $X = \bar{X} + X'$, where X' represents the anomaly, $\bar{X}$ the trajectory, and X is any of the three variables: ω , S_{BT} , and S_{NS} . t is time and $s=1$ yr. The evolution of the anomalies is given by the linearization of (1.5) around the long trajectory. This diagnostic shows a regular structure in phase space (Fig. 1.3 right). Positive/negative values suggest divergence/convergence of close trajectories. This explains how the evolution of the inter-member standard deviation increases and decreases during its journey along divergent and convergent regions of the strange attractor, respectively (Fig 1.3 bottom left) and suggests

that some regions of phase space, some states of the system, are more predictable than others depending on whether small disturbances between trajectories grow or decay.

1.2.3 Discussion of conceptual approaches

With these two idealized models we have illustrated the two forms of chaos, stochastic and deterministic. These models fundamentally differ in their predictability. Whereas the stochastic framework suggests that the integration of the atmospheric stochastic forcing by the ocean induces a monotonic divergence of the trajectory (solely controlled by the oceanic adjustment timescale), the deterministic framework shows a more intricate behavior. Indeed, the latter shows that both divergence and convergence of trajectories can occur depending on the state of the system itself, despite an overall divergence of the trajectory on long timescales. This suggests that, unlike in the stochastic framework, in a deterministic framework some states are more predictable than others, and some might even be fully predictable (the trajectories converge with a negligible uncertainty). This result is consistent with the analysis of Slingo and Palmer (2011) using the chaotic model of Lorenz (1963).

Clearly these two conceptual models are limited in their application to the real world, despite being extremely useful for illustrating different types of error growth (i.e., due to internal or external processes). Hence we will now focus on more realistic studies that focus on assessing the predictability of the AMOC.

1.3 Assessing the predictability

In this section, we will first describe modes of variability affecting the AMOC and the precursors of its changes. This will deal with processes contributing to the predictability of the AMOC. Then we will focus on a range of more theoretical studies determining the growth of small disturbances potentially affecting the AMOC and hence limiting its predictability. In the last part we will focus on describing the current pragmatic method, ensemble experiments using state-of-the-art climate models, to estimate AMOC predictability and synthesizing our current knowledge gathered through this method.

1.3.1 Contributing factors

Precursors of AMOC changes

One source of predictability of the AMOC is the existence of precursors of its changes. Precursors can be determined in a statistical sense or in a dynamical sense. For the former, the link between the precursor and AMOC changes is not formally identified and it is only demonstrated that the occurrence of the two with a delay is robust in a statistical sense (there might not be a causal link between the precursor and AMOC changes). On the other hand, precursors might also be determined in a dynamical sense, suggesting that the precursors are a (proximate) cause of AMOC changes. In both cases and because of

nonlinearities of the system, there might exist a wide range of precursors depending on the initial magnitude of the AMOC (i.e., its position in phase space) and the nature of the change. Indeed, precursors of an AMOC decrease might be different if the AMOC is already low or high. There is a large body of work focused on determining precursors of AMOC changes. Here we have selected a few recent examples.

Swingedouw et al. (2015) suggest that volcanic eruptions can play a significant role in the timing of AMOC variations with a 15 yr delay. They suggest a succession of events that lead to a change in the AMOC. All these events can be considered as potential precursors of AMOC changes: East Greenland Current weakening with 12-15 years delay, Labrador Sea buoyancy change with a delay of 10-12 years, subpolar convection with a delay of 7-9 years, for instance. This suggests a range of precursors and so of monitoring regions useful to anticipate AMOC changes. However here the links are only robust in a statistical sense (i.e., there is no demonstration that the precursors induce the AMOC changes through a physical mechanism).

Another recent study suggests that changes in deep buoyancy in the Labrador Sea is well correlated with AMOC changes one year later in a high resolution coupled-model (Robson et al., 2014b). The study also suggests that the link is consistent with observations. This implies that deep water in the Labrador Sea can be used to predict AMOC changes one year in advance. Despite suggesting a plausible physical explanation for this link, by construction the only robust demonstration of this study is a statistical link.

On the other hand, a body of work has characterized precursors in the causal sense. One tool that is particularly well fitted for this purpose is the “adjoint model”, which allows the computation of the sensitivity of the AMOC to changes. Indeed, this method is by construction causal but is limited by its intrinsic assumption of linearity (i.e., precursors need to be small compared to the mean oceanic flow). In this context, Bugnion and Hill (2006) identify a range of surface oceanic precursors of AMOC changes, in an idealized flat-bottom rectangular-basin configuration of a general circulation model. These precursors include wind stress over the subtropical gyre on interannual timescales and surface heat flux gradient across the North Atlantic Current on decadal timescales. In a realistic configuration and focusing on surface precursors, Sévellec et al. (2008) and Sévellec and Fedorov (2015a) suggest that the most important precursor acts on a decadal timescale and corresponds to either a surface temperature or salinity perturbation in the subpolar region along the east coast of Greenland. Czeschel et al. (2010) confirm this result and also identified the east coast of Europe as a potential temperature precursor to AMOC changes on decadal timescales. Heimbach et al. (2011) exhaustively characterize the different precursors of AMOC variations and their associated timescale (we refer the reader to this study for a full description of the precursors) and suggest the use of the adjoint method to design an efficient system for monitoring and anticipating AMOC variations.

Since the AMOC has been conjectured to be a multiple equilibria system (Stommel, 1961; Marotzke and Willebrand, 1991; Rahmstorf, 2000; Rahmstorf et al., 2005), its predictability is also affected by our ability to anticipate an abrupt jump from its current equilibrium to another. Indeed the changing climate, through freshening at high latitudes, might be able to push the AMOC beyond a threshold or a tipping point where it will be and re-

main shutdown (e.g., Rahmstorf, 1995; Barreiro et al., 2008; Dijkstra, 2007; Sévellec et al., 2010). This is especially timely since direct and indirect measurements suggest that the AMOC is gradually weakening (Smeed et al., 2014; Rahmstorf et al., 2015), and it is anticipated to slow-down during this century (Cheng et al., 2013). Hence, detection of Early Warning Signals (e.g., Livina and Lenton, 2007; Dakos et al., 2008; Scheffer et al., 2009; Lenton, 2011) of an AMOC abrupt shutdown has become an extensive and fruitful area of current research. This research aims to determine precursors through statistical (Cimadoribus et al., 2013) or dynamical (Sévellec and Fedorov, 2014) approaches that assess the proximity of an AMOC dramatic event. In particular it has been suggested that whereas statistical early warning signals are weak (Cimadoribus et al., 2013) the ocean vertical stratification can be a good precursor of a dramatic collapse of the AMOC (Sévellec and Fedorov, 2014). Although promising, so far these methods remain limited in their applications. Moreover, although the AMOC is anticipated to decrease, possibly dramatically, over the 21st century (Cheng et al., 2013), the risk of an abrupt collapse is perceived to be limited since it has only been experienced during glacial periods rather than during interglacial periods such as the present time (Dansgaard et al., 1993; Bond et al., 1997; Grootes and Stuiver, 1997; Bond et al., 1999). Indeed, whereas the bistability of the AMOC during the last glacial period appears to be a plausible hypothesis confirmed by a wide range of studies (e.g., Sakai and Peltier, 1999; Colin de Verdière, 2007), it remains an open question with conflicting evidence for the current climate state (e.g., Arzel et al., 2010; Colin de Verdière and te Raa, 2010; Huisman et al., 2010; Cimadoribus et al., 2012; Sévellec and Fedorov, 2015b).

Modes of variability

Beyond precursors, it has been suggested that internal modes of variability or harmonic oscillations of the ocean lead to an increase of predictability (Griffies and Bryan, 1997). The rationale behind this result is that oscillations, even if damped, repeat themselves in time and so are a source of predictability. As discussed earlier and demonstrated by Chang et al. (2004), this is not the case if one measures the predictability through its Predictive Power, which only measures the relative increase in variance. However other predictability metrics, such as Autocorrelation Coefficient, take into account the absolute changes of the system, which is also dictated by modes of variability. In this context robust internal modes of variability will increase the predictability by inducing changes with a well defined timing if one initializes these modes accurately (i.e., setting their phases correctly). Hence we will now discuss state-of-the-art knowledge of modes of variability of the AMOC relevant on decadal timescales.

In the absence of direct observations of AMOC variability on decadal to multi-decadal timescales (Rapid observations being only a decade old, McCarthy et al., 2012; Srokosz and Bryden, 2015), many studies concentrate on dominant climate modes in the Atlantic that may be linked to the AMOC. Climate modes are spatially coherent structures that described large-scale variations of SST. The Atlantic Multidecadal Oscillation (AMO) is one of these climate modes particularly coherent in observations and believed to re-

flect variations in the AMOC strength (Schlesinger and Ramankutty, 1994; Delworth and Mann, 2000; Zhang, 2007; Roberts et al., 2015). Despite the relatively short duration of the observational period and the limited accuracy of longer proxy records, it is typically associated with periods between 50 to 70 yr (Kushnir, 1994) and is possibly paced by volcanic eruptions (Oterrá et al., 2010; Swingedouw et al., 2015, 2017). In climate models the AMO is associated with variations in the AMOC intensity of the order of 1 Sv (Knight et al., 2005). Potentially, the AMO can exert strong impacts on climate, affecting hurricane activity over the North Atlantic (Goldenberg et al., 2001) and precipitation over North America (Enfield et al., 2001; Sutton and Hodson, 2005). Knight et al. (2006) linked the AMO and precipitation over North-East Brazil, the African Sahel (also Ward, 1998) and North-West Europe. Msadek and Frankignoul (2009) showed global impacts of this variability, and indirectly of the AMOC, on SST and surface precipitation reaching the Indian Ocean and Central Asia. Sutton and Hodson (2003) linked the AMO and climate change over the North Atlantic.

Observational studies show not only the existence of 50-70 yr variability, but also variability in the 20-30 year band (Fig. 1.4 or Frankcombe et al., 2008, for instance). These two ranges of frequencies contribute together to 54% of the annual AMO index and up to 85% of its decadal variations (Fig. 1.4, see Appendix B for methodological details). The shorter-period, interdecadal variability can be easily identified if one uses variations in temperature or Sea Level Height (SLH) in latitudinal bands instead of using average sea surface temperature. By analyzing SLH variations, Frankcombe and Dijkstra (2009) find a coherent westward propagating mode with a 20-30 yr period in both data and climate models. The authors hypothesize that the AMO might have a strong signature at 20-30 yr in addition to the 50-70 yr band more commonly associated with the AMO. Many coupled General Circulation Models (GCMs) display similar 20-30-year variability (Muir and Fedorov, 2017) – CCSM3 for example (Danabasoglu, 2008). In addition, Latif et al. (2007) discusses the possibility of quasi-decadal variability in the Atlantic.

Despite these clarifications, the physical mechanisms controlling the internal mode(s) in the North Atlantic, and even whether there are several modes or none at all, are still being strongly debated (IPCC, 2013). A review of different mechanisms in a hierarchy of models ranging from idealized to comprehensive is given by Yoshimori et al. (2010). We also refer the reader to Buckley and Marshall (2016) for a discussion of modes of variability affecting the AMOC. Hence, even if one focuses on the AMOC variability occurring on decadal to multidecadal time scales (i.e., excluding centennial or millennial, for instance), there are a large number of oceanic processes and feedbacks that can potentially generate temporal variations in the North Atlantic (Dijkstra and Ghil, 2005). A far from exhaustive list of general ideas for the mechanisms of decadal climate variability in the Atlantic would include:

- Large-scale basin modes (Cessi and Paparella, 2001; Ben Jelloul and Huck, 2003, 2005);
- Effects of the Great Salinity Anomalies or similar anomalies (Belkin et al., 1998; Häkkinen, 1999; Haak et al., 2003; Zhang and Vallis, 2006);

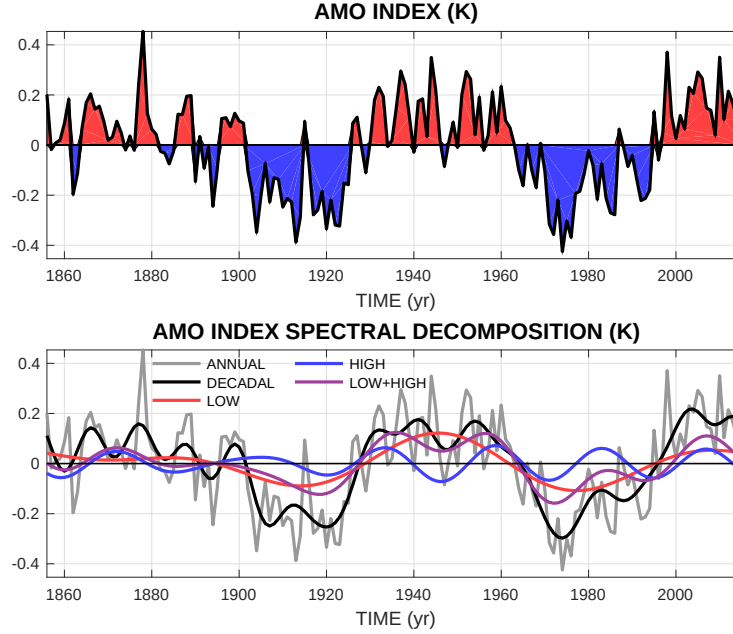


Figure 1.4: AMO index from 1856 to 2015 following Enfield et al. (2001). Here AMO index is the annual-mean sea surface temperature anomaly averaged over the North Atlantic from 0 to 70°N. (top) positive/warm and negative/cold periods are highlighted in red and blue, respectively. (bottom) Spectral decomposition of the annual (grey line) and decadal (black line) AMO index in terms of its low frequency component (50-70 year band, red line), of its high frequency component (20-30 yr band, blue line), and of the sum of these two components (purple line). Low and high frequencies contribute together to 54% and 85% of the annual and decadal AMO index variances (i.e., coefficient of determination of 0.54 and 0.85), respectively.

- Episodic deepening of the mixed layer in the areas of deep convection (Spall, 2008; Deshayes et al., 2009);
- Baroclinic instability of large-scale Rossby waves propagating on the thermocline (Chen and Ghil, 1995; Colin de Verdière and Huck, 1999; Huck and Vallis, 2001; Sévellec and Fedorov, 2013a; Ortega. et al., 2015; Sévellec and Huck, 2015);
- Interaction between the ocean zonal and meridional circulations (te Raa and Dijkstra, 2002; Dijkstra et al., 2006);
- The “intergyre” gyre effect (Marshall et al., 2001);
- Western boundary buoyancy forcing (Buckley et al., 2012).

A number of studies focus specifically on the AMO-like variability (Yoshimori et al., 2010; Latif, 1997). Several particular mechanisms for the AMO have been proposed, from changes in the subtropical gyre (Dong and Sutton, 2005; D’Orgeville and Peltier, 2009; Cheng et al., 2004) to variability of the subpolar gyre that alters the heat budget of the Labrador Sea (Danabasoglu, 2008). Other studies focus more on the westward-propagating mode with the 20-30 yr period discussed earlier (Huck et al., 1999; Colin de Verdière and Huck, 1999; Huck and Vallis, 2001; te Raa and Dijkstra, 2002; Dijkstra et al., 2006; Sévellec and Fedorov, 2013a; Ortega. et al., 2015; Sévellec and Huck, 2015). This absence of a consensus on the mechanism driving AMOC variability on decadal timescales strongly limits our ability to predict its associated changes, since we do not know how to efficiently initialize it.

1.3.2 Theoretical investigations of error growth

Despite this lack of understanding of modes of variability, the predictability can still be assessed as suggested in section 1.2. Indeed we can measure the increase in the system variance regardless of our knowledge of the physics or existence of internal modes, following the original idea of Lorenz (1965). In this part of the manuscript we will describe a robust methodology to measure growth of perturbations (i.e., divergence of trajectories) and its application for assessing decadal predictability of the AMOC in ocean models. Generalized Stability Analysis (GSA) has provided new tools for understanding stability and perturbation growth in geophysical fluid dynamics (e.g., Farrell and Ioannou, 1996a,b; Palmer, 1999). For the ocean circulation, GSA has been used in a number of applications ranging from mesoscale eddies to the El Niño-Southern Oscillation and the thermohaline circulation (Moore et al., 2003; Tziperman and Ioannou, 2002). Unlike classical stability analysis, which treats asymptotic stability, GSA considers perturbation growth over a finite time and allows for transient growth in a time-varying system. Consequently, the method can consider the sensitivity of changing climate on different time scales, making it relevant to predictability (Palmer, 1999). However, it is not yet a method that is widely spread in the oceanographic and climatic communities and few groups use this method in realistic settings.

In this section we will first describe the mathematical principle behind GSA and then discuss its application in the context of the AMOC, which has given us new and robust insights on its predictability.

Method

The prognostic equations of a fully nonlinear model can be written as a general non-autonomous (i.e., changing with time) dynamical system:

$$d_t |\mathbf{U}\rangle = \mathcal{N}(|\mathbf{U}\rangle, t), \quad (1.7)$$

where $\mathcal{N}$ is a time-dependent nonlinear operator, $|\mathbf{U}\rangle$ is a state vector consisting of all prognostic variables, and t is time. For an ocean GCM, the state vector is comprised of the three-dimensional fields of temperature, salinity, meridional and zonal velocity, together with the two-dimensional field of barotropic streamfunction or sea surface height. Since we study a finite-dimensional vector space, we can also define a dual vector $\langle \mathbf{U}|$ through the Euclidean scalar product $\langle \mathbf{U}|\mathbf{U}\rangle$.

We decompose the state vector as $|\mathbf{U}\rangle = |\bar{\mathbf{U}}\rangle + |\mathbf{u}\rangle$, where $|\bar{\mathbf{U}}\rangle$ is the non-linear trajectory (i.e., the background state) and $|\mathbf{u}\rangle$ is a perturbation. The temporal evolution of the perturbation follows a linear equation:

$$d_t |\mathbf{u}\rangle = \mathbf{A}(t) |\mathbf{u}\rangle, \quad \mathbf{A}(t) = \left. \frac{\partial \mathcal{N}}{\partial |\mathbf{U}\rangle} \right|_{|\bar{\mathbf{U}}\rangle}, \quad (1.8)$$

where $\mathbf{A}(t)$ is a Jacobian matrix (a function of the trajectory $|\bar{\mathbf{U}}\rangle$). We also defined an adjoint to the Jacobian matrix as $\langle \mathbf{a}|\mathbf{A}|\mathbf{b}\rangle = \langle \mathbf{b}|\mathbf{A}^\dagger|\mathbf{a}\rangle$, where $|\mathbf{a}\rangle$ and $|\mathbf{b}\rangle$ are two anomalous state vectors, $\dagger$ denotes the adjoint defined through the Euclidian scalar product $\langle \mathbf{a}|\mathbf{b}\rangle = \langle \mathbf{b}|\mathbf{a}\rangle$.

We can integrate (3.2) to obtain an explicit expression for the perturbation as a function of time (Farrell and Ioannou, 1996b):

$$|\mathbf{u}(t_2)\rangle = \mathbf{M}(t_2, t_1) |\mathbf{u}(t_1)\rangle, \quad (1.9)$$

where $\mathbf{M}(t_2, t_1)$ is called the propagator of the linearized dynamics from time t_1 to time t_2 . If the propagator (or the Jacobian Matrix) does not commute with its adjoint, $\mathbf{M}^\dagger(t_2, t_1)\mathbf{M}(t_2, t_1) \neq \mathbf{M}(t_2, t_1)\mathbf{M}^\dagger(t_2, t_1)$, the dynamics is non-normal and more inclined to variability than normal system (Ioannou, 1995).

We also define a norm for the state vectors: $\langle \mathbf{u}|\mathbf{S}|\mathbf{u}\rangle$. Finally, to evaluate the optimal growth of small initial disturbances, we define the Lagrangian function as:

$$\mathcal{L}(|\mathbf{u}(t_i)\rangle, \gamma) = \langle \mathbf{u}(t_m)|\mathbf{S}|\mathbf{u}(t_m)\rangle - \gamma (\langle \mathbf{u}(t_i)|\mathbf{S}|\mathbf{u}(t_i)\rangle - \epsilon^2), \quad (1.10)$$

where t_i is the initial time (when the optimal initial perturbation is applied), t_m is the maximization time (when the norm reaches its maximum), and γ is a Lagrange multiplier. (Note that in general the norm applied in the first and second terms of the right hand side can be different.) ϵ is a parameter associated with the normalization constraint:

$$\langle \mathbf{u}(t_i) | \mathbf{S} | \mathbf{u}(t_i) \rangle = \epsilon^2. \quad (1.11)$$

That is, ϵ measures the magnitude of the initial perturbation. Thus, the goal here is to maximize the norm subject to this normalization constraint. Hence, if the norm applied in the first and second terms of the right hand side of (3.20) are equivalent, the optimization identifies the maximum growth of the perturbation measured through this norm. This growth would be given by γ .

From expression (3.20) and the optimization condition $d\mathcal{L}=0$ the optimal initial perturbations are computed as

$$\mathbf{M}^\dagger(t_m, t_i) \mathbf{S} \mathbf{M}(t_m, t_i) | \mathbf{u}_{\{t_i, t_m\}}^{\text{opt}}(t_i) \rangle = \gamma \mathbf{S} | \mathbf{u}_{\{t_i, t_m\}}^{\text{opt}}(t_i) \rangle. \quad (1.12)$$

This expression gives the solution of the optimization problem, through the generalized eigenvalue problem of $\mathbf{M}^\dagger(t_m, t_i) \mathbf{S} \mathbf{M}(t_m, t_i)$, also called Singular Value Decomposition (SVD, Farrell and Ioannou, 1996b), with the eigenvectors $| \mathbf{u}_{\{t_i, t_m\}}^{\text{opt}}(t_i) \rangle$ and eigenvalues γ . It depends both on the initial time t_i and the maximization time t_m , so that an eigenvalue problem must be solved for each studied delay.

Application

This method has been applied in the context of the AMOC by Tziperman and Ioannou (2002) in an idealized box-model (Stommel, 1961). They show, in the context of the AMOC, that small disturbances are able to grow on transient timescales, despite the system being asymptotically stable. This study has been extended using more complex models by Zanna and Tziperman (2005), Zanna and Tziperman (2008), and Zanna et al. (2011), generalizing this transient growth behaviour up to primitive equation models. However the model configuration remains idealized (rectangular basin with flat bottom). Indeed solving an eigenvalue problem, such as (3.12), is numerically costly and the computation of SVDs has not been performed in the most realistic state-of-the-art models yet.

Two alternative approaches have been suggested to overcome the numerical cost of generalized stability analysis and allow the computation of transient growth in state-of-the-art realistic model settings. The first alternative was suggested by Sévellec et al. (2007) and Sévellec et al. (2009). The authors demonstrated that the use of a linear cost function [first term on the right handside of (3.20)] instead of a norm to measure the transient change leads to an explicit solution (versus an eigenvalue problem). This is a lot more efficient to compute and so also tractable on a range of transient delays in realistic configurations (Sévellec et al., 2008). This method is a synthesis of GSA and adjoint sensitivity analysis (Marotzke et al., 1999; Czeschel et al., 2010) and suggests an optimal transient growth of the AMOC on decadal timescales from a surface perturbation (Sévellec and Fedorov, 2015a). Despite making progress toward realism, this method is limited to coarse resolution forced ocean models. Indeed, given its linear framework, either atmospheric or oceanic small scale instabilities will continuously grow and will eventually dominate the model response.

Another alternative method has been suggested by Tziperman et al. (2008). The authors used a reduced-space representation of a coupled ocean-atmosphere model, based on a finite sum of Empirical Orthogonal Functions (EOFs) for the 3-dimensional temperature and salinity fields. This method has the advantage of representing the tangent linear and adjoint models without explicitly using them. Hence it allows the computation of SVDs in coupled (and potentially high resolution) models. The authors show that the optimal transient growth occurred between 5 and 10 years, providing an estimated time for the AMOC predictability in the North Atlantic. Following a similar approach Hawkins and Sutton (2009a) and Hawkins and Sutton (2011) suggested an optimal transient growth at 35 years. It is interesting to note that these studies have shown the importance of either convection sites or deep oceanic regions, consistently with Sévellec and Fedorov (2015a, 2017), who suggested enhanced sensitivity of the AMOC to deep density anomalies because of their longer residence time (Sévellec and Fedorov, 2013b).

Following the same approach, and taking advantage of the fact that it does not require the explicit linear and adjoint models, Zanna (2012) applied the same method using Sea Surface Temperature reanalysis. The author suggested the existence of an optimal transient growth of surface average temperature anomalies between 3 to 4 years, possibly limiting the predictability of this metric. Overall all these approaches have shown promising results to assess the climate predictability by allowing computation in state-of-the-art climate models and even the direct use of observations, albeit restricted to well monitored ones (i.e., SST). However these methods still have shortcomings. For example the reduction to a finite sum of EOFs has been suggested to be far from ideal to represent the system non-normality (Farrell and Ioannou, 2001), the latter being at the core of transient growth. Also this approach, as others discussed so far, remains in a linear framework, despite the system being potentially strongly nonlinear. There exist methods to fully deal with nonlinearities but, as with SVDs, they are still so far restricted to relatively idealized models (e.g., Mu et al., 2004; Zu et al., 2016).

1.3.3 Ensemble experiments

As mentioned earlier, an alternative approach exists that is not bounded by the technical difficulties of these theoretical investigations. This more pragmatic approach is often referred to as ensemble experiments (Hurrell et al., 2006; Meehl et al., 2009, 2015). It consists of setting up a large number of numerical simulations differing slightly in their initial conditions to represent the inherent state-estimation uncertainty (Boer, 2000, 2004, 2011). These studies are often done in a “perfect model approach”, assuming the initial condition is the only uncertainty (e.g., there is no uncertainty linked to model error and/or to forcing scenario). This allows focusing on the role of initial condition uncertainty. The predictability is estimated by statistically diagnosing the ensemble spread of the numerical simulations. The rationale behind this method is that by sampling effectively the initial condition uncertainty, we will have a good representation of the evolution of the probability density distribution. The spreading of the latter in phase space represents the growth of the uncertainty, and so is a measure of the system predictability.

Unlike theoretical methods previously described, this pragmatic method is relatively easy to apply and has allowed the study of climate predictability since the 1990s (Griffies and Bryan, 1997). However, it still faces an important challenge, which is the way to set the initial conditions or the ensemble design. Several techniques exist to sample as accurately as possible the initial condition uncertainty from adding random perturbations to the atmospheric state (e.g., Persechino et al., 2013) to switching day-lagged atmospheric states (e.g., Griffies and Bryan, 1997), for instance. However these methods mostly concentrate on the atmospheric state (with little or no consideration of the initial condition uncertainty in the oceanic state). In this context, Du et al. (2012) and Germe et al. (2017b) have attempted to rationalize the role of the oceanic uncertainty in the ensemble design. Du et al. (2012) suggested that oceanic uncertainty modifies the decadal climate predictability, Germe et al. (2017b) also suggested a direct stimulation of atmospheric divergence by oceanic perturbation even though it was located in the deep ocean.

In an early attempt to characterize the AMOC predictability, Griffies and Bryan (1997) suggested that the main mode of variability for the SST is predictable for 5-7 yr. They noted that this value can be reduced in the absence of periodic decadal oscillations in the system. Later, Collins and Sinha (2003) suggested the predictability of the AMOC for one to two decades, or even up to 50 yr under certain conditions. This was confirmed by Pohlmann et al. (2004) who suggested predictability on multidecadal timescales for SST and SAT in the North Atlantic and Nordic Seas. However, Pohlmann et al. (2004) show SAT over land predictability is limited to maritime-influenced regions, unlike Collins and Sinha (2003) who suggested that AMOC predictability leads to predictability of Western Europe SAT variations. Generalizing these studies through a multimodel-ensemble study, Collins et al. (2006) show that the AMOC and SAT in the North Atlantic is predictable on interannual to decadal timescales. Building on this, Keenlyside et al. (2008) suggested that this potential predictability, especially in the North Atlantic, can be converted to routine decadal climate prediction with a good initialization of the ocean state. More recently, Msadek et al. (2010) suggested AMOC predictability up to 2 decades ahead and similar predictability for upper ocean heat content variations. These results were questioned by Teng et al. (2011) who suggested, in climate change ensemble experiments, that the AMOC might only be predictable for a decade before the long secular forcing dominates its behaviour. In the same context, the authors show that the upper 500 m oceanic temperature in the North Atlantic might be predictable by several more years. Following the idea of Keenlyside et al. (2008), Swingedouw et al. (2013) suggested that prediction can be improved by an accurate constraint of the SST toward observations. In particular this study shows a significant increase in predictive skill of the 2-m air temperature regions bordering the North Atlantic, and a good AMOC predictive skill for up to 4 years. This contrasts with the result of Persechino et al. (2013) using exactly the same model, who show that the AMOC has an average predictive skill of 8 years whereas surface temperature in the North Atlantic can have skill up to 2 decades.

Despite this body of evidence suggesting the potential decadal predictability of climatically relevant large scale features (Latif et al., 2006), there is little quantitative agreement between studies. Thus, after decade-long progress by scientific community, going beyond

qualitative assessment remains a timely scientific objective. One possible reason for this is the shortcoming of current ensemble experiment design. Due to computational limitation most ensembles are designed with ~ 10 members at best. This might be enough for a qualitative assessment of the predictability but not for a quantitative one. Indeed, in the idealized model described in section 1.2.1, the qualitative aspect of the error growth is well captured with a relatively low number of members (i.e., 8-10 members). On the other hand, several tens if not more than a hundred members are needed for an accurate quantitative estimation of predictability (Fig. 1.5). Since this result is obtained with a linear 1 degree-of-freedom system, it is expected that it would be more dramatic in the context of climate models, which have a significantly higher number of degree-of-freedom (e.g., there are more than ~ 2 million semi-independent variables just for the ocean-only model, NEMO-ORCA2, Madec, 2008). Hence, it appears that quantitative assessments might be reached in the near future by increases in computational power, or alternatively through a breakthrough in the way ensembles are designed (Baehr and Piontek, 2014; Ramanova and Hense, 2015).

1.4 State-of-the-art and current challenges of inter-annual to decadal prediction

1.4.1 Decadal prediction systems: hindcasts and forecasts

Decadal prediction, as opposed to predictability poses its own set of problems, but carries the potential to provide societally relevant and useful forecasts. The first decadal prediction studies were published about a decade ago (Smith et al., 2007; Keenlyside et al., 2008; Pohlmann et al., 2009), following pioneering perfect model predictability studies such as those by Griffies and Bryan (1997), Collins and Sinha (2003), and Collins et al. (2006) mentioned in the previous section. The new challenges were initialization, radiative forcing, model bias, drift from initialization, validation and skill assessment and computational expense, the latter limiting both model complexity and resolution, and ensemble size. The main effort has been focussed on global mean near surface temperature, but more recently predictions are beginning to include regional temperature and other variables such as rainfall and winds and ocean circulation such as the AMOC.

1.4.2 Initialization and data assimilation

Most effort has concentrated on initialisation of the ocean component of the climate system, since it has the largest heat capacity, and the bulk of the memory of the system resides there. More recently there has been research on the importance of initialising other components of the system, including land and sea ice.

As regards the ocean, two main methods are available: full field and anomaly initialisation. In the former, an estimate of the full initial temperature and salinity fields (and in some cases other state variables such as sea-surface height, zonal and meridional velocities) is

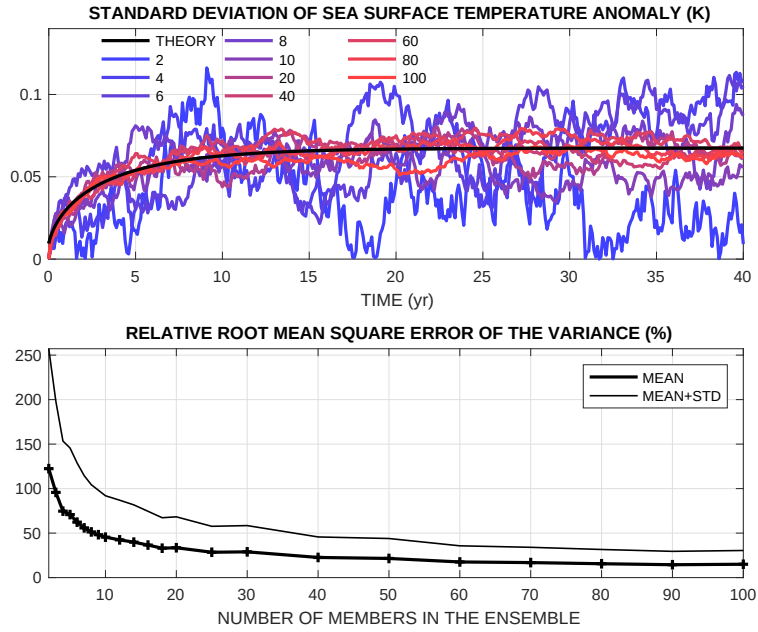


Figure 1.5: (top) Evolution of the standard deviation of Sea Surface Temperature anomaly for the stochastic idealized model from section 1.2.1 using different sizes of ensemble (the number of members are indicated in the legend) together with the theoretical results from (1.2). (bottom) Convergence of the variance to the theoretical value as a function of the number of members for the ensemble. The convergence is measured by the root mean square distance between ensemble and theoretical value divided by the time-mean of the theoretical variance. To obtain accurate statistics each ensemble has been reproduced 100 times for ensembles with less than or equal to 20 members and 20 times for ensembles with more than 20 members, the results are displayed in term of the average and average plus one standard deviation over the different members.

obtained on the model grid (methods described below) and used as the initial condition. In the latter case, anomalies with respect to an observed climatology are prepared on the model grid and added to a model climatology. Although both methods have their proponents, the most comprehensive study to date comparing the two methods concludes that there is little to choose from in terms of decadal prediction skill (Hazeleger et al., 2013).

The problem of obtaining observation-based data on the model grid is common to both approaches and there are a variety of methods in use. There are two broad choices: one is to use products based only on observations using statistical methods (e.g., optimal interpolation) with no dynamical model (such as an ocean GCM), although a model may be used to estimate spatial covariances which are inputs to the statistical model (e.g., Smith et al., 2007). The second and by far more common approach is to use a dynamical model to assimilate a subset of available observations in order to provide an estimate of the ocean state at the desired starting point of the forecast. The assimilation methods vary from simple nudging towards observed SST fields (e.g., Keenlyside et al., 2008), to nudging to 3D temperature and salinity (Smith et al., 2007, 2010), to more complex Data Assimilation (DA) methods such as three-dimensional (Balmaseda et al., 2013) and four-dimensional (Wunsch and Heimbach, 2007; Mochizuki et al., 2016) variational data assimilation. Another approach is to avoid altogether the need for assimilation of ocean data and instead to simply specify surface fluxes (with strong relaxation to observed SST) or to specify near surface meteorological variables such as winds and allow the model fluxes to vary based on bulk formula. Doblas-Reyes et al. (2011) and Matei et al. (2012) demonstrate cases where assimilation of subsurface observations has no significant effect on decadal prediction skill. In contrast Dunstone and Smith (2010) and Counillon et al. (2014) suggest that for some aspects (such as the AMOC) use of subsurface ocean observations is beneficial.

The initial atmosphere state has historically been considered less important for decadal forecasting (e.g., Dunstone and Smith, 2010, show that the atmospheric state has little impact beyond the first year in the DePreSys forecast system). Nonetheless many forecast systems are initialized with atmospheric observation such as atmospheric reanalyses. For example, Smith et al. (2007) used ECMWF reanalyses (e.g., Anderson et al., 2007). In decadal forecasting, the main emphasis involving atmosphere initial conditions is now on coupled ocean-atmosphere data assimilation (see below).

Sea ice initialization is still being developed, for example Guemas et al. (2014) found a modest increase in forecast skill for Arctic sea ice extent and surface air temperature in the EC-Earth climate model when initializing with a sea ice field, strongly constrained to be consistent with observed atmosphere and ocean observations compared to using one that had been obtained from a free running (no data assimilation) forced ocean-ice model hindcast, and thus weakly constrained and less realistic. However the Antarctic sea ice extent was slightly less skillfully predicted and there was very little effect on the global surface air temperature forecast skill.

Coupled ocean-atmosphere data assimilation methods are also gaining ground and continue to be an active area of research. To date proof of concept studies have been per-

formed using intermediate complexity coupled models. Data assimilation can be weakly coupled, where the coupled model is used to provide a background state, or it can be strongly coupled where covariances between atmosphere and ocean variables are used so that atmospheric observations can directly affect the ocean state and vice versa. A number of studies indicate that strongly coupled data assimilation can improve the mean state of both atmosphere and ocean over the weakly coupled case, notably that of Sluka et al. (2016), where only atmosphere observations are assimilated and result in an improved ocean state, with subsequent feedback to further improve the atmospheric state. Tardif et al. (2014) investigate the value of coupled DA for accurate simulation of the AMOC. However coupled DA appears particularly useful when few ocean observations are available, hinting that more comprehensive observations of the ocean [e.g., below the current depth range (0-2000m) of the Argo fleet] may be as or more important for decadal forecasting than coupled DA techniques. Simpler procedures such as that of Thoma et al. (2015), where the coupled system is spun up using observed windstresses to drive the ocean, are still being tested and the Thoma et al. (2015) scheme shows some promise in the Pacific sector, but less in the Atlantic.

Land is usually not directly initialized but initialization of ocean and atmosphere implicitly initializes land, for example Smith et al. (2010) apply nudging to observations (reanalysis) in order to initialize the atmospheric state, which results in the modification of the land state to achieve energy and moisture balance with the atmosphere. Explicit initialization is becoming more feasible using for example satellite observations of soil moisture, but at the time of writing has not been incorporated into operational decadal forecast systems. For decadal forecasts generation of ensemble members is still usually ad hoc (e.g., using a number of nearby initial atmospheric start dates from a control simulation, or random perturbation to the SST field). This ad hoc approach carries a risk that the forecast ensemble will underestimate the true width of the climate variable probability density at any given lead time. Methods such as those of Karspeck et al. (2013) and Baehr and Piontek (2014) attempt to circumvent this risk by using more advanced techniques such as the ensemble Kalman Filter and breeding methods respectively. Similar arguments apply to the ocean, and methods such as GSA (Section 3.2) may be applied to maximise the spread in forecasts at a given lead time. However, such methods might be counter productive in some cases, since many forecast systems already overestimate the variability (Eade et al., 2014, also see Section 4e for further details).

1.4.3 Radiative forcing

For hindcasts, the usual treatment of radiative forcing has been to specify atmospheric concentrations of anthropogenic and volcanic aerosols, anthropogenic CO₂ and other greenhouse gases and variations of incident solar radiation at the top of the atmosphere from the best available observations. Uncertainty in estimates of these quantities may influence the accuracy of the initial conditions as they input to the assimilation process, and will also directly influence hindcasts. Particularly for aerosols, some significant uncertainty remains over the actual evolution of the atmospheric aerosol burden over the period of

historical observations. This uncertainty is being addressed for example through ongoing research into the chemical and physical processes responsible for aerosol concentration (e.g., cloud microphysics). Revised estimates of aerosol historical evolution are likely to be available in the next few years (Mills et al., 2016). However, even if the correct aerosol and gases were present, there would still be uncertainty in how the climate system responds to them (especially clouds). Mitigating this is the fact that the observations used in initialising the models are affected by the history of forcing and have the correct response.

Major volcanic eruptions cannot at present be predicted in advance and are neglected for decadal forecasts. However, should a major eruption occur, a forecast could soon be run to get some idea of the impacts over the next few years. On longer timescales the probability of major volcanic eruptions, such as Mt Pinatubo in 1991 can be fitted to high accuracy with a Poisson distribution (Roscoe, 2001). For decadal timescales, small to moderate eruptions have a significant cumulative effect (Timmreck et al., 2016) and ongoing work suggests these have a similar statistical distribution to the major ones (A. Schmidt, unpublished data). These distributions could potentially be incorporated into next generation decadal forecast systems.

Although there have been numerous studies and the general consensus is that the AMOC response consists of an increase in the first decade following eruption followed by a decline, a wide range of behaviour and mechanisms is found with potential dependence on the prevailing climate state at the time of the eruption (Mignot et al., 2011), seasonality, subsequent and previous eruptions (Swingedouw et al., 2015). Different models favour different mechanisms, ranging from the direct effect of high latitude cooling (Jones et al., 2005), to indirect effects resulting from modifications to the hydrological cycle (precipitation, evaporation, and runoff – Iwi et al., 2012), a combination of both effects (Pausata et al., 2015) to sea ice changes (Swingedouw et al., 2015), depending also on the strength of the eruption.

Solar forcing is generally related to the observed changes in radiation following the 11-year solar cycle (Willson, 2014) and for forecasts is set to be identical to the previous 11-year cycle. Before the launch of satellite radiometers (late 1970s) no direct measurements of solar irradiance at the top of atmosphere were available and the irradiance is reconstructed from sunspot observations.

Greenhouse gas concentration variations are likely to have a minor effect over a given decadal forecast period, hence the exact choice of future scenario is not very important on such timescales (Fig. 1.1 and Hawkins and Sutton, 2009b). Nonetheless, even if the predictability of the AMOC arising from initialisation may fall away on the time scales of years to decades, considerable (and non-trivial) predictability arises from the greenhouse gas forcing, especially on multidecadal timescales.

1.4.4 Model bias, drift and bias correction

The key point here is that models are an imperfect representation of the real world. Hence the model attractor is different from the real world attractor. Thus when initializing

with observations, models tend to drift to the preferred state of the model. This is typically corrected with a lead dependent bias correction constructed from the mean difference between a large number of hindcasts and the observations at a given lead time. Fig. 1.6 illustrates the point with a postulated attractor corresponding to “reality” and another corresponding to the model (both based on the model of Sévellec and Fedorov, 2014, introduced in section 1.2.2 and displayed in Fig. 1.3). In the case illustrated in the top left panel, the coloured trajectories represent “reality” whilst the grey contours represent a “model” attractor, derived from the real one via a strain transformation. Initial conditions derived from observations (points A and B) are displaced with respect to the model attractor and the model quickly evolves to a state on the model attractor (points A’ and B’ respectively). Depending on the nature of the attractor, the drift may be to the “correct” state; i.e., an analogue of the real initial state (B’), or it may evolve to an “incorrect state” (A’). If the drift results in the model moving to an analogous state to the initial observations, and the model attractor is similar to reality we may obtain a skillful forecast if the drift is subtracted from the model predictions and an estimate of the drift is given by the mean displacement of the model predictions with respect to the observations. In the case illustrated, an average mean bias correction would work quite well for the initial state B, less well for initial state A. Problems with a simple bias correction occur if the model attractor is translated (lower left panel), rotated (top right), or distorted (strain transformation already discussed) compared to the the real attractor. In the general case, the model attractor will be related to the real one by some combination of these three transformations.

Fig. 1.6 illustrates that the model bias may vary, not only with lead time, but with model state (e.g., whether or not the model is in an El Niño state, Choudhury et al., 2016) and whether the local model trend is different from the true trend (see Meehl et al., 2014). For decadal forecasting in particular, there is now strong evidence that a large number of start dates (at least yearly) is at least as important as increasing ensemble size and that a more sophisticated bias correction is beneficial. A further point to note (bottom right panel) is that even in the relatively simple case of a constant translation of the model attractor relative to reality, the forecast bias can vary with model state, as the rate and direction of the initial drift will depend on the local topology of the attractor (i.e., line AA’ is not parallel to BB’).

A way forward is to address the biases of individual models (e.g., Huang et al., 2015) in order to bring their attractors closer to the real world attractor, inferred, as far as possible, from observations. This process of model improvement is ongoing, but often incremental (e.g., Knight et al., 2014) hence research on more accurate bias adjustment continues (Narapusetty et al., 2014) and detailed analysis of drift dynamics is required to focus model development efforts where they will have most effect in reducing drift (Sanchez-Gomez et al., 2016).

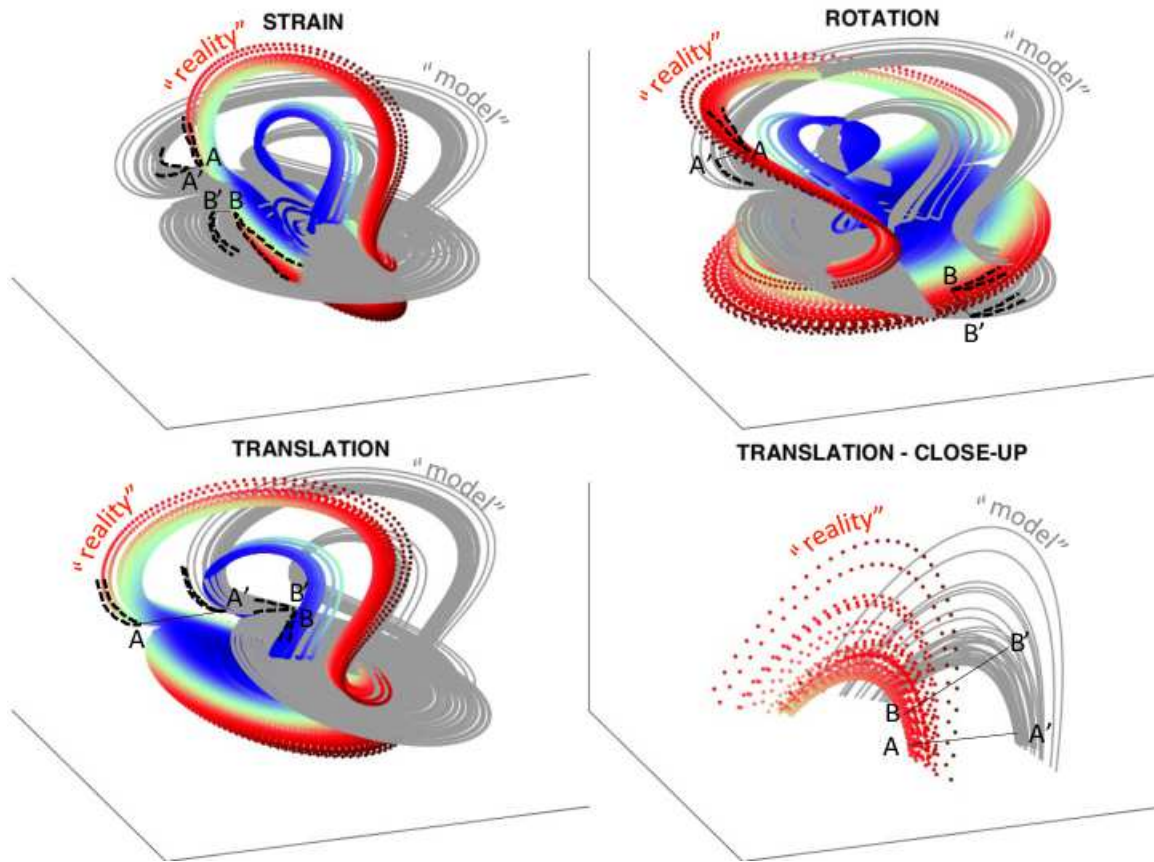


Figure 1.6: Illustration of the effects of model bias on decadal prediction skill and error growth. (Top right) the attractor for the deterministic chaos model from Fig. 1.3 is shown in colour, representing the real world attractor. Grey lines trace the attractor of a postulated biased model, related to the real world attractor by a strain transformation. A decadal prediction system is initialized at two points on the real world attractor (points A and B). Dashed lines from these points indicate the envelope of the trajectories from points A and B if the model was unbiased. Thin black lines indicate rapid drift of the model state from the initialization (points A and B) to points on the model attractor (A' and B'). The biased model then predicts a spread of trajectories from these points, represented by the dashed lines originating from points A' and B'. Similar diagrams represent the effect of the biased model attractor related to the real world attractor by a rotation (top right) and a translation (bottom left). The final panel (bottom right) shows an enlargement of part of the bottom left panel and indicates that even for a simple translation, the direction of the drift from initialization to the model attractor may vary for different initialization points.

1.4.5 Validation and skill

Validation methods for decadal forecasts has drawn heavily from the experiences of the numerical weather prediction and seasonal forecasting communities, although relatively simple measures of skill such as Anomaly Correlation Coefficient (ACC) and Root Mean Square Error (RMSE) remain in common use (Collins, 2002). A key issue of debate is the relationship between potential predictability and actual skill (Boer et al., 2013) as the difference between these two measures is thought by many to indicate the possibility of improving forecast systems; e.g., by modifying the observing system, initialization/assimilation procedures or model biases (Kumar et al., 2014). The implications of comparing an ensemble mean variable from a forecast system with the single realisation obtained from observations have yet to be fully explored but are understood in terms of a predictable component (“signal”), common to all ensemble members in a forecast and an unpredictable component which varies randomly between ensemble members (“noise”). Eade et al. (2014), make a key assumption that a correlation between observational time-series and an ensemble mean timeseries obtained from a forecast is indicative of the real-world predictable component for that variable, allowing an assessment of the relative sizes of the predictable and unpredictable components in models versus observations. This gives a useful procedure for identifying regions where model signal-to-noise ratio is either too high or too low and is likely to result in deeper understanding of the processes giving rise to predictability in different regions, and the fidelity of model representations of these processes. However a number of subtle issues still need to be explored, for example a problematic element of the analysis of Eade et al. (2014) is that the predictable element of the real world must be estimated from the model prediction system itself, and different systems may thus give very different estimates. Set against this is evidence that many forecast systems overestimate the variability (e.g., particularly in the North Atlantic for predictions of the SAT and NAO, see Eade et al., 2014). In view of this, maximising the ensemble spread may in fact be problematic, rather it may be desirable to apply post-processing adjustments to bring the ensemble spread in line with expectation based on observations.

On the other hand, skill scores have been calculated for decadal hindcasts produced by operational decadal forecasting systems. Simple measures such as the RMSE and ACC are sufficient to indicate whether initialization results in enhanced skill (beyond persistence) over uninitialized forecasts. It has been widely noted that the North Atlantic subpolar gyre region displays enhanced skill in decadal forecasts of SST and upper ocean heat content compared to most other regions of the globe (van Oldenborgh et al., 2012; Pohlmann et al., 2009; Robson et al., 2017). Taking the Pohlmann et al. (2009) results, the North Atlantic ACC for SST averaged over 50-10°W and 0-60°N is of order 0.7 for pentadal time scales, clearly superior to persistence (0.2) or a trend forecast (0.0). Detailed process studies (Robson et al., 2012a,b, 2014a) indicate that decadal changes in the AMOC, and its associated horizontal heat transport, are to a large degree responsible for this predictability.

This attribution raises the question of the predictability of the AMOC. This question

is quite difficult to address because of the historical paucity of direct measurements of the AMOC. The RAPID array at 26°N has now been in place for 13 years and hence direct validation of decadal forecasts will soon be a possibility, albeit with low statistical confidence. For the near to medium term future we will be reliant on ocean reanalyses (also known as ocean syntheses) which provide a dynamically consistent ocean state constrained to be as close to observations as possible. These therefore provide AMOC estimates (which can themselves be validated against observations at 26°N) for a far longer period than possible using the RAPID array. Whilst the differences were not as high as with SST or upper ocean heat content, Pohlmann et al. (2013) demonstrated using a multimodel approach that initialized decadal prediction systems were better at predicting AMOC estimates from the GECCO ocean synthesis than persistence. There is a far wider variety of ocean syntheses now available and intercomparison between these will give a better idea of the actual variation of the AMOC, with estimated uncertainty bounds from the mid 20th century onwards.

1.4.6 Continued development of state of the art prediction systems

Meehl et al. (2014) provide a useful summary of decadal prediction systems which contributed to the CMIP5 (Coupled Model Intercomparison Project Phase 5) decadal prediction experiments. At the time of that review, many of the groups had not published individual accounts of their latest results and in the intervening period these have been published (Knight et al., 2014; Msadek et al., 2014; Wu et al., 2015). Interesting recent uses and advances include work by García-Serrano et al. (2015) on predictability of the AMO, by Müller et al. (2014) extending decadal predictions as far back as 1901, and by Timmreck et al. (2016) suggesting that volcanic aerosols play a more important role than previously thought, including over European land areas. Potential advances in forecasting techniques are discussed by for example Mochizuki et al. (2016), on four-dimensional variational data assimilation, and Smith et al. (2016) who discuss the benefits of improved vertical resolution of the stratosphere as well as horizontal resolution in the atmosphere and ocean and initialization of sea ice.

A recent development is the extension of the scope of decadal prediction beyond atmospheric temperature to include a larger number of societally relevant variables such as soil moisture, vegetation and wildfire (Chikamoto et al., 2015), sea ice (Germe et al., 2014; Huang et al., 2015), salinity (Huang et al., 2015), windstorm activity (Nissen et al., 2014), precipitation over land (e.g., Rodríguez-Fonseca et al., 2015, on West African drought), and North Atlantic Circulation (Smith et al., 2016).

1.5 Discussion

In our changing climate, there is an increasing societal demand to predict its variations for well-planned mitigation and cost efficient adaptation. On interannual to decadal

timescales accurate prediction of global atmospheric temperature comes from the correct estimation of the “internal” variability rather than the exact future CO₂ emission pathway (Fig. 1.1 left). On timescales longer than decades the main signature of “internal” variability is located in the North Atlantic region (Fig. 1.1 right), with a pattern typical of surface atmospheric temperature variations associated with AMOC changes (Drijfhout, 2015). Hence decadal AMOC variations appear to be a key factor for prediction of the atmospheric temperature on decadal timescales. From a physical point of view, because of its northward heat transport, the AMOC is central to the climatic system of the North Atlantic and its neighboring regions. Here we have described and discussed the state-of-the-art knowledge on the decadal variability and predictability of this large scale ocean circulation.

We have first defined the two paradigms (stochastic and deterministic) that explain the difficulty of predicting the climate system. For both paradigms, we have introduced an idealized model to illustrate how external or internal processes lead to uncertainty in climate prediction. As always, in the real climate system the truth lies in the middle. This means that both sources of uncertainty limit our ability to predict the climate on decadal timescales.

After these conceptual considerations we have discussed the contributing and limiting factors of decadal predictability of the AMOC. Contributing factors can be divided in two types: modes of variability and precursors. The former suggests that harmonic variations, that recur with a well-established period, contribute to accurate predictions. In the same manner, determining precursors, and using them as early warning signals for AMOC changes, increases our ability to predict the system. On the other hand, we have discussed the mechanisms that lead to uncertainty in climate prediction. Here, we have described both theoretical and pragmatic investigations.

Finally, we have described the state-of-the-art of AMOC prediction on interannual to decadal timescales. In particular, we have described decadal prediction systems and the use of data assimilation to accurately constrain the initial conditions. The latter induces a current challenge for prediction systems. Indeed, because of the inherent mismatch between the natural states of the models used for prediction and the (mostly oceanic) observations used to constrain their initial conditions, there are strong drifts during prediction, that need to be corrected. These drifts are linked to the recovery of numerical models from their observation-constrained attractor to their inherent attractor during the unconstrained prediction phase. We have also included a brief review of future developments in climate prediction such as new techniques to avoid such strong drifts, and also the extension of the scope of predictions to others climatically relevant variables such as sea ice, storm activity, and precipitation over land.

The topic of predictability is extremely dense and we have only described a few methods. For example, there is another method that diagnoses the predictability based on long model control simulations (e.g., DelSole and Tipett, 2009; Branstator and Teng, 2012a, 2014). This method is particularly efficient since it does not require new simulations and takes advantage of already existing ones. However the assumption that the level of variability is constant is central to the method and remains an inherent shortcoming

in a changing climate. Another existing method is the best analogs approach which, after identifying past climate states close to the current one, assesses the likely future evolution of the climate based on typical outcomes of these close climate states (e.g., Barnett and Preisendorfer, 1978). On a more theoretical level, Pullback Attractor (e.g., Ghil et al., 2008; Chekroun et al., 2010; Sévellec and Fedorov, 2015b; Pierini et al., 2016) and Transfer Operator (e.g., Tantet et al., 2015) methods, although they have not yet been applied to state-of-the-art climate models, already demonstrate promising results regarding the characterization of predictability.

AMOC predictability is intrinsically linked to climate predictability on decadal timescales. However the former remains poorly quantitatively assessed, with as yet no consensus in the scientific community. Since the technical expertise required for accurate quantitative prediction goes beyond the confines of climate science, significant advancements are likely to come from future methodological and/or computational-power breakthroughs.

Appendix 1.A: CMIP5 Multimodel-analysis

The diagnostics shown in Fig. 1.1 follow the method of Sévellec et al. (2016). Hence the text below is derived from there with minor modifications.

The analysis performed in this study followed a multimodel approach (i.e., all the statistics are estimated from ensemble averages of 20 climate models). The SAT data for pre-industrial control (with fixed present-day atmospheric GHG concentrations), historical, Representative Concentration Pathways 2.6, 4.5 (RCP2.6 and RCP4.5, two “stabilisation scenarios”), 6.0 (RCP6.0 “intermediate scenarios”), and 8.5 (RCP8.5, “business as usual”) simulations were gathered from the CMIP5 database (Taylor et al., 2012). The 20 models are: (1) ‘IPSL-CM5A-MR’, (2) ‘CCSM4’, (3) ‘EC_EARTH’, (4) ‘GFDL-CM3’, (5) ‘MIROC5’, (6) ‘BNU-ESM’, (7) ‘CSIRO-MK3’, (8) ‘CanESM2’, (9) ‘MPI-ESM-MR’, (10) ‘INMCM4’, (11) ‘CNRM-CM5’, (12) ‘GISS-E2-R’, (13) ‘BCC-CSM1-1’, (14) ‘ACCESS1-3’, (15) ‘CMCC-CESM’, (16) ‘FGOALS-g2’, (17) ‘FIO-ESM’, (18) ‘MRI-CGCM3’, (19) ‘NorESM1-M’, (20) ‘MOHC_HadGEM2-ES’. Except for RCP8.5 some models were missing: for RCP2.6 – (10,14,15); for RCP4.5 – (15); for RCP6.0 – (3,4,6,8,9,10,11,14,15,16,18).

To evaluate the decadal “internal” variability, we use global SAT (i.e., a global spatial horizontal averaging of SAT) from the pre-industrial control simulations for each of the 20 models. To evaluate the uncertainty of the “internal” variability for different prediction lead times, we first filter the global SAT using a low pass-filter with a varying cut-off frequency set between 2.5 and 80 years and based on a simple step function (i.e., removing all frequency components above the cut-off frequency but not affecting lower frequencies). Then, a probability density function of the time derivative of this filtered SAT is built to represent the standard deviation of warming and cooling events equal or longer than cut-off frequency. This standard deviation is our measure of the “internal” variability for different prediction lead times and is evaluated through the 20-member multimodel mean. For the external forcing uncertainty, we use linear trends evaluated using a linear re-

gression of global average SAT for RCP2.6, RCP4.5 RCP6.0, and RCP8.5 at different prediction lead times. The “forced” linear trend corresponds to the 20-member multi-model mean. This allows the removal of out-of-phase “internal” decadal variability, hence limiting its impact on the linear trend. We chose to use a single realization for each model, and not all the different initial condition members where available, to avoid biasing our study toward the models which were run with a larger number of ensemble members. Then we compute the uncertainty in the “external” forcing by computing the inter-scenario variance of the multimodel-mean trend evaluated at different prediction lead times (i.e., from 2.5 to 80 yr).

Finally, comparing the variance of the “external” forcing and of the “internal” variability, we build the relative contribution to the total variance of “external” forcing and of “internal” variability as a function of different prediction lead times (left of Fig. 1.1). Assuming linearity and independence of the variances, the total variance is the sum of the variance induced by the “external” forcing and by the “internal” variability.

To compute the intensity of the local decadal “internal” variability we reproduce the global analysis for 10 yr prediction lead time only, but at a local level (right of Fig. 1.1). For that we use SAT from pre-industrial control simulations after linear interpolation from the respective native model grid to a regular $2^\circ \times 2^\circ$ grid. We also provide the 20-member multimodel standard deviation as a measure of the model error (Fig. 1.7).

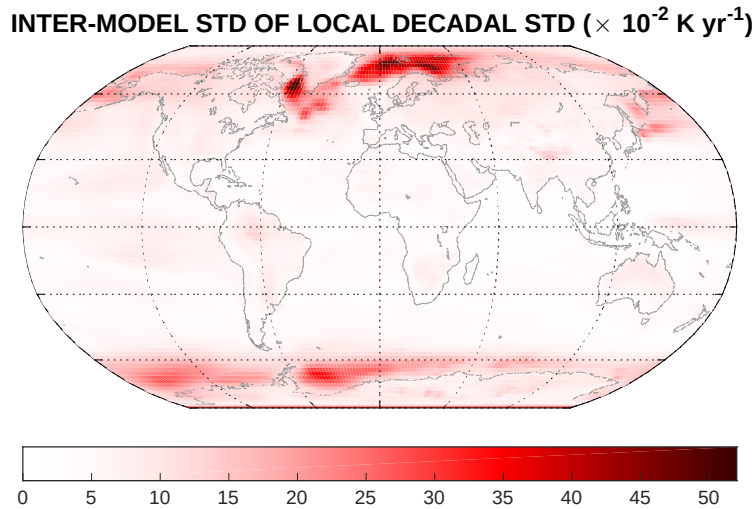


Figure 1.7: Multi-model standard deviation of local standard deviation of SAT decadal trend from CMIP5 pre-industrial control simulations. This figure can be compared to the multi-model mean given in Fig. 1.1 right.

Appendix 1.B: AMO index

To represent the AMO index we used the unsmoothed detrended AMO index from www.esrl.noaa.gov/psd/data/timeseries/AMO/, following Enfield et al. (2001). This index is the annual mean Sea Surface Temperature averaged in the Atlantic from 0 to 70°N. The decadal values is obtained through a low pass filter set at 10 yr. The low and high frequency components are obtained by applying a band pass filter set between 20 and 30 yr and between 50 and 70 yr, respectively. This procedure removes all frequency components above the maximum cut-off frequency and below the minimum cut-off frequency maximum, leaving unaffected frequencies inside the minimum and maximum cut-off frequencies.

Chapter 2

Sensitivity to Initial Condition

This work was done in collaboration with A. V. Fedorov

2.1 Summary

In this chapter, we investigate the excitation of decadal variability, and predictability of the ocean climate state in the North Atlantic. Specifically, we compute initial Linear Optimal Perturbations (LOPs) in temperature and salinity that vary with depth, longitude and latitude and evaluate the maximum impact on the ocean of these perturbations in a realistic ocean general circulation model. Our computations of the LOPs involve a maximization procedure based on Lagrange multipliers in a non-autonomous context. To assess the impact of these perturbations we use four different measures of the North Atlantic ocean state: meridional volume and heat transports (MVT and MHT), and spatially-averaged sea surface temperature (SST) and ocean heat content (OHC). We show that these metrics are dramatically different with regard to predictability. Whereas OHC and SST can be efficiently modified only by basin-scale anomalies, MVT and MHT are also strongly affected by smaller-scale perturbations. This suggests that instantaneous or even annual-mean values of MVT and MHT are less predictable than SST and OHC. Only when averaged over several decades the former two metrics have predictability comparable to the latter two, which highlights the need for long-term observations of the Atlantic meridional overturning circulation in order to accumulate climatically relevant data. Our study also suggests that initial errors in ocean temperature of a few millikelvins, encompassing both the upper and deep ocean, can lead to ~ 0.1 K errors in the predictions of North Atlantic sea surface temperature on interannual timescales. This transient error growth peaks for SST and OHC after about 6 and 10 years, respectively, implying a potential predictability barrier.

2.2 Introduction

Climate prediction on a range of timescales is progressing rapidly, with the ultimate goals extending from seasonal to decadal and centennial prediction (IPCC, 2013). In the context of the ongoing climate change, it has been argued that on seasonal to decadal timescales uncertainty in climate prediction is related to the internal variability but on longer timescales (century) to the future scenario of CO₂ emissions (Hawkins and Sutton, 2009b). Thus, the latter uncertainty is linked to societal choices, whereas the former is related to the adjustment of the climate system, which in numerical climate simulations depends, to a large extent, on the evolution of small errors in the initial conditions. In the present study we will focus on this particular uncertainty in decadal prediction, which presumably sets the limits on the predictability of the climate system at these timescales. Despite notable improvements, our ability to predict climate for the next decade or so remains an open question in the scientific community, even though potentially it could have large societal implications. For example, predicting the Atlantic Multidecadal Oscillation/Variability (Kushnir, 1994; Delworth and Mann, 2000) would be highly desirable as it influences hurricane activity (Goldenberg et al., 2001) and precipitation over North America and Europe (Sutton and Hodson, 2005).

There are two main reasons why errors or offsets in the model initial conditions result in uncertainty. First, they can induce a phase-shift in the simulated climate variability. For instance, two identical, perfectly periodic oscillators initialized at different phases would evolve conserving their initial phase difference, leading to uncertainty. However, this uncertainty remains relatively constant in time and can be reduced, or even removed, by a good initial phasing of the climate system, *i.e.* by using more accurate initial conditions. Therefore, efforts have been directed to improve the accuracy of the initialization of numerical models used for climate prediction, and so to limit any phase shift in the simulations. This is done both by increasing the coverage and number of in situ measurements (*e.g.* the Array for Real-time Geostrophic Oceanography program), and by developing different state-estimate methods (*e.g.* variational assimilation, Weaver et al., 2003).

The second, perhaps a more challenging problem is related to the growth of small errors in non-linear systems such as climate. This concept, popularized as the "butterfly effect", follows the pioneering work of Lorenz (1963) on atmospheric dynamics. The error growth sets a theoretical limit on prediction, which for weather forecasting is estimated at about two weeks (Epstein, 1988). For the climate system, wherein the short-term weather uncertainty averages out, this timescale remains largely unknown.

To address this problem, the scientific community has followed two main approaches. One approach involves ensemble experiments with slightly different initial conditions representing inherent errors in the model initialization. This pragmatic approach often concentrates on atmospheric errors, while the ocean is kept unperturbed initially. Another, more rigorous approach relies on computing small initial disturbances that can induce the maximum change in the system after a specified time, which is done by using the generalized stability analysis (GSA, Farrell and Ioannou, 1996a,b). Unlike the linear stability analysis (Strogatz, 1994), which only considers the system's asymptotic behaviour, GSA

accounts for transient phenomena, making it perfectly suitable for predictability studies. The main drawback of GSA against ensemble experiments is the assumption that the evolving perturbations remain small. Such an assumption, allowing the linearization of the system's equations around the climatological basic state, is valid for decadal variability of the Atlantic meridional overturning circulation (AMOC), which is typically weak compared to the mean AMOC intensity (*e.g.* 1 Sv *vs.* 10 Sv in the IPSL-CM5 climate model, Mignot and Bony, 2013), in particular during the Holocene period (Tziperman, 1997).

Despite being less rigorous than GSA, studies using ensemble experiments have substantially improved our understanding of climate predictability. In an early paper, Griffies and Bryan (1997) suggested that the AMOC intensity had a predictability timescale on the order of 10-20 yr, whereas sea surface temperature was predictable at 5-7 yr. However, during intervals when multi-decadal oscillatory variations were less prominent, predictability was strongly reduced because oceanic response to atmospheric noise dominated (Hasselmann, 1976). More recently, Collins and Sinha (2003) argue that AMOC variations are potentially predictable one to two decades into the future, and this decadal predictability may lead to climate predictability for Western Europe. This result however contradicts the study of Pohlmann et al. (2004), who suggest that, although ocean surface temperatures over the North Atlantic (as well as the Southern Ocean) exhibit predictability on multi-decadal timescales, surface air temperatures are only predictable over the ocean and maritime-influenced regions of Europe. Along the same lines, a series of studies suggest that AMOC variations, surface temperature, subsurface temperature, and upper ocean heat content are potentially predictable on decadal timescales (Collins et al., 2006; Msadek et al., 2010; Teng et al., 2011; Zanna, 2012).

Overall, all these studies agree on a possible decadal predictability for the ocean; however, the quantitative details of this predictability remain contradictory. For example, whereas Persechini et al. (2013) suggest that the AMOC averaged over 5 to 10 years has a higher predictability than ocean heat content, Branstator and Teng (2014) argue that in the far North, Atlantic ocean surface temperatures have predictability higher than the AMOC (up to 2 decades *vs.* 8 years, respectively). Note that some of these studies use either experiments with a small number of ensemble members or truncated principle component analyses, known to underestimate error growth (Farrell and Ioannou, 2001).

In recent years the use of GSA in the context of ocean circulation and climate dynamics on decadal timescales has seen an increase in popularity (*e.g.* Tziperman and Ioannou, 2002; Zanna and Tziperman, 2005; Sévellec et al., 2007; Tziperman et al., 2008; Zanna and Tziperman, 2008; Sévellec et al., 2008; Hawkins and Sutton, 2009a; Sévellec et al., 2009; Hawkins and Sutton, 2011; Zanna et al., 2011; Sévellec and Fedorov, 2015a). In these studies two different methods are typically used: Singular Value Decomposition (SVD, *e.g.* Tziperman and Ioannou, 2002) and Linear Optimal Perturbation(s) (LOP, *e.g.* Sévellec et al., 2007). Whereas both methods deal with the transient growth of small perturbations, they have subtle differences in the way predictability is defined and estimated. The SVD method uses standard tools of linear algebra and requires solving an eigenvalue problem. The LOP method is derived from a more pragmatic approach

that relies on an optimization problem whose solutions describe the maximum linear growth of a chosen climatic variable over a given time. Schematically, in the context of predictability, SVD yields error growth evaluated via a quadratic norm (Lorenz, 1965), whereas LOPs yield the full error bar (the upper bound) on a chosen climatic variable (Taylor et al., 2012). LOPs can also incorporate different additional constraints imposed in the process of optimization. Note that the two methods are not mutually exclusive, and for further comparison we refer the readers to Sévellec et al. (2007). LOPs can be more efficiently computed since they are given by explicit solutions of the optimization problem (*vs.* solutions of an eigenvalues problem for SVD). Due to this efficiency and the physical significance of the full error bar for a practical estimation of predictability, here we use the LOP method.

There exists a long history of perturbation studies based on similar methodological principles as the LOP approach described here. Indeed, since the pioneering work of Lorenz (1965), Singular Vectors have been broadly used to estimate error growth. Lorenz's work has been followed by a long series of other studies, especially in the context of predictability in atmospheric sciences. To name a few relevant approaches, we could cite Lyapunov vectors (*e.g.* Yoden and Nomura, 1993) and finite time normal modes (*e.g.* Frederiksen, 2000) used in a linear framework, or bred vectors (*e.g.* Baehr and Piontek, 2014) and Conditional Nonlinear Optimal Perturbations applicable in a nonlinear framework (*e.g.* Mu and Zhang, 2006; Zu et al., 2016).

In the current study, we will compute and apply LOPs to diagnose the predictability of several major metrics of the ocean state in the North Atlantic. Hence, predictability is assessed here by estimating the upper bound of the impact on the system of small disturbances. We will show that this predictability strongly depends on the metric used to measure the ocean state. Sea surface temperature and ocean heat content are predictable up to 6 and 10 years, respectively, whereas instantaneous values of ocean meridional volume and heat transports appear to be unpredictable. The predictability of the latter two metrics is improved by applying decadal averaging to the metrics – thus averaged MVT and MHT might be predictable on decadal timescale. Note that the above numbers describe the worst-case scenario based on the upper bound of error growth. Whether in practical cases a particular metric can be predicted for longer lead times will depend on how strongly model initialization errors project on the optimal perturbations.

The structure of the paper is as follows. In section 2.3, the ocean model, configuration and seasonal cycle are described. The results of the analysis are given in section 2.4. An idealized model is used in section 2.5 to confirm analytically and further rationalize the main findings of the study. In section 2.6, implications of the results for ocean predictability will be given. Finally, section 3.6 includes discussions, conclusions and directions for future work.

2.3 The ocean model, configuration and seasonal cycle

The ocean GCM we use in this study, and its tangent linear and adjoint versions, has been employed in several previous studies by the same authors. In particular, they studied ocean sensitivity to initial perturbations in surface temperature and salinity (Sévellec et al., 2010; Sévellec and Fedorov, 2013a,b, 2015a) and to constant in time surface buoyancy fluxes (Sévellec and Fedorov, 2016). While the model and the seasonal cycle it generates have been described in those studies, in this section we reproduce these descriptions for completeness.

2.3.1 The model configuration

In this study we use the ocean General Circulation Model (GCM) OPA 8.2 (Océan Parallélisé, Madec et al., 1998) in its 2° global configuration (ORCA2, Madec and Imbard, 1996). There are 31 levels in the vertical – with the layer thickness varying from 10 m at the surface to 500 m at depth. The rigid-lid approximation is used. The primitive equations are discretized using an Arakawa C-grid and the z-coordinates.

Although a number of models participating in the last IPCC report (AR5) used a 0.25° resolution in the ocean, our study takes advantage of a model with a lower resolution of 2° (note that the IPSL climate model uses the OPA as its oceanic component with the same 2° resolution, IPSL-CM5, Marti et al., 2010). The main reason for having the relatively coarse resolution is to avoid the small-scale baroclinic instability existing in eddy-permitting or eddy-resolving models. Within the linear framework of this study, such instability would not saturate, and as we are interested in large-scale basin adjustment would contaminate the solutions of our experiments.

The present model configuration uses the following parameterizations: convection is parameterized by an increase in vertical diffusion when ocean stratification becomes unstable; double diffusion is taken into account by two different terms for mixing temperature and salinity; eddy-induced velocities are described by the Gent and McWilliams (1990) expression; viscosity coefficients follow the turbulent closure scheme of Blanke and Delecluse (1993) and are functions of longitude, latitude and depth; and diffusion for temperature and salinity acts along isopycnal and diapycnal coordinates (Redi, 1982).

The linear and adjoint models are provided by the OPATAM code (OPA Tangent Adjoint Model, Weaver et al., 2003). The tangent linear model is a linearization of the OPA's primitive equations of motions with respect to the ocean seasonally-varying basic state.

In the present study, we use either the flux boundary conditions (with surface heat and freshwater fluxes specified) or mixed boundary conditions (with an SST restoring term is used in addition to specified freshwater fluxes). The restoring coefficient for SST is set to $40 \text{ W m}^{-2} \text{ K}^{-1}$ and $27.7 \text{ mm day}^{-1} \text{ psu}^{-1}$ (following standard values, Madec et al., 1998). The time-mean ocean fluxes were computed by running the full nonlinear model forced with a combination of the prescribed climatological fluxes and restoring terms (restoring to the climatological seasonal cycle). This latter approach produces a realistic seasonal

cycle used by the linear and adjoint models, while reducing the damping and allowing SST anomalies to develop more easily (Huck and Vallis, 2001; Arzel et al., 2006; Sévellec et al., 2009), for details see below.

Several additional approximations have been introduced for the tangent-linear and adjoint models: viscosity coefficients in the momentum equations, tracer diffusivities, and eddy-induced advection are calculated only for the basic ocean state – further variations in those coefficients are neglected.

2.3.2 The model seasonal cycle

The seasonally-varying basic state of the ocean, also referred to as the annual model "trajectory", is obtained by the direct integration of the OPA model subject to the climatological surface boundary forcing (varying with the annual cycle). In particular, we used the ECMWF heat fluxes averaged in the interval from 1979 to 1993, the ERS wind stress blended with the TAO data between 1993 - 1996, and an estimate of the climatological river runoff. In addition, we applied a surface temperature restoring to the Reynolds climatological values averaged from 1982 to 1989, together with a surface salinity restoring to the Levitus (1989) climatology (we emphasize that the restoring term can be switched off in the experiments with the linear and adjoint models). A mass restoring term to the Levitus climatological values of temperature and salinity was applied in the Red and Mediterranean Seas. Starting with the Levitus climatology as the initial conditions, the model produces a quasi-stationary annual cycle of the ocean basic state after 200 years of integration.

The Atlantic meridional overturning circulation in the full ocean GCM (Fig. 2.1) is characterized by a northward mass transport above the thermocline, a southward return flow below 1000-1500 m and extending to about 3000 m, and a recirculation cell 3000 m associated with the Antarctic Bottom Water. The maximum volume transport of the AMOC is around 14 Sv, which is slightly below but still within the errorbars of the observations (*e.g.* 18 ± 5 Sv, Talley et al., 2003). The AMOC poleward heat transport reaches 0.8 PW at 25°N, whereas estimates from inverse calculations and hydrographic sections give 1.3 PW at 24°N (Ganachaud and Wunsch, 2000).

As expected, the SST field develops a strong meridional gradient in the northern Atlantic, especially across the North Atlantic Current (NAC); it also develops a salinity maximum at about 20°N (Fig. 2.1). The plot of barotropic streamfunction shows an intense subtropical gyre and a weaker subpolar gyre centered at about 60°N. The two gyres are separated by the Gulfstream and the NAC. Overall, the full nonlinear model produces a realistic (seasonally-varying) basic state of the ocean. Next, we will conduct a generalized stability analysis of this ocean state, focusing on the ocean response to three-dimensional initial perturbations in temperature and salinity.

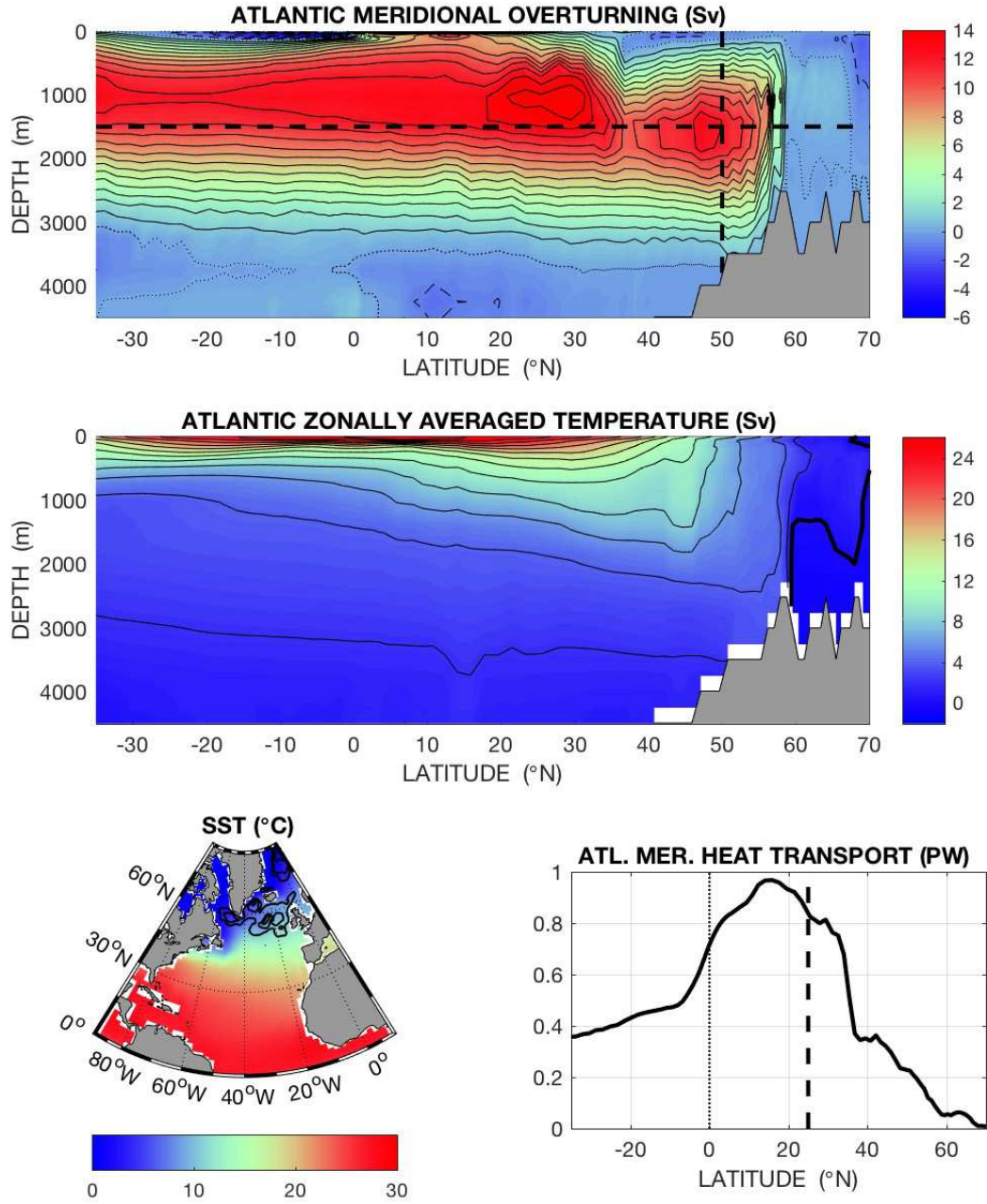


Figure 2.1: The climatological basic state of the ocean in the Atlantic as reproduced by the full GCM. (Top) Zonally-averaged streamfunction of the Atlantic meridional overturning circulation; contour intervals (CI) are 1 Sv; plain, dashed and dotted lines indicate positive, negative and zero values. (Middle) Zonally-averaged temperature; CI are 2°C, the thick solid line corresponds to 0°C. (Bottom left) Sea surface temperature (colors) and ocean mixed layer depth (contours); CI are 250 m. (Bottom right) The Atlantic ocean meridional heat transport as a function of latitude. In the top and bottom-right panels, the thick dashed horizontal and vertical lines indicate the latitudes and depth where MVT and MHT are estimated. These two variables along with spatially-averaged OHC and SST in the North Atlantic are used as measures in the optimization problem. The figure is modified from Sévellec and Fedorov (2015a).

2.4 Optimal initial perturbations

2.4.1 Mathematical approach

The goal of these calculations is to obtain initial thermohaline (temperature and salinity) perturbations that will induce the largest change in the North Atlantic ocean state after a given time within a linear framework. Here, we apply and extend the methodology originally proposed by Sévellec et al. (2007) and Sévellec et al. (2008). The text below follows from the derivation of Sévellec and Fedorov (2015a) with a numbers of modifications pertinent to the present study.

The prognostic equations of the full nonlinear model can be written as a general non-autonomous dynamical system:

$$d_t |\mathbf{U}\rangle = \mathcal{N}(|\mathbf{U}\rangle, t), \quad (2.1)$$

where $\mathcal{N}$ is a time-dependent nonlinear operator, $|\mathbf{U}\rangle$ is a state vector consisting of all prognostic variables, and t is time. The state vector is comprised of the three-dimensional fields of temperature, salinity, meridional and zonal velocity, together with the two-dimensional field of barotropic streamfunction. Since we study a finite-dimensional vector space, we can also define a dual vector $\langle \mathbf{U}|$ through the Euclidian scalar product $\langle \mathbf{U}|\mathbf{U}\rangle$. We decompose the state vector as $|\mathbf{U}\rangle = |\bar{\mathbf{U}}\rangle + |\mathbf{u}\rangle$, where $|\bar{\mathbf{U}}\rangle$ is the non-linear annual trajectory (*i.e.* the climatological background state) and $|\mathbf{u}\rangle$ is a perturbation. The temporal evolution of the perturbation follows a linear equation:

$$d_t |\mathbf{u}\rangle = \mathbf{A}(t) |\mathbf{u}\rangle, \quad \mathbf{A}(t) = \left. \frac{\partial \mathcal{N}}{\partial |\mathbf{U}\rangle} \right|_{|\bar{\mathbf{U}}\rangle}, \quad (2.2)$$

where $\mathbf{A}(t)$ is a Jacobian matrix (a function of the trajectory $|\bar{\mathbf{U}}\rangle$). We also define an adjoint to the Jacobian matrix as $\langle \mathbf{a}|\mathbf{A}|\mathbf{b}\rangle = \langle \mathbf{b}|\mathbf{A}^\dagger|\mathbf{a}\rangle$, where $|\mathbf{a}\rangle$ and $|\mathbf{b}\rangle$ are two anomalous state vectors, $\dagger$ denotes the adjoint defined through the Euclidian scalar product $\langle \mathbf{a}|\mathbf{b}\rangle = \langle \mathbf{b}|\mathbf{a}\rangle$.

After assuming that perturbations are and remain small, we can integrate (3.2) to obtain an explicit expression for the perturbation as a function of time (Farrell and Ioannou, 1996b):

$$|\mathbf{u}(t_2)\rangle = \mathbf{M}(t_2, t_1) |\mathbf{u}(t_1)\rangle, \quad (2.3)$$

where $\mathbf{M}(t_2, t_1)$ is called the propagator of the linearized dynamics from time t_1 to time t_2 . Following the study of Sévellec and Fedorov (2013a), using the exact same numerical model, we know that the propagator does not commute with its adjoint, *i.e.*

$\mathbf{M}^\dagger(t_2, t_1)\mathbf{M}(t_2, t_1) \neq \mathbf{M}(t_2, t_1)\mathbf{M}^\dagger(t_2, t_1)$. This defines the non-normality of the dynamics. To evaluate the ocean state, we will compare four different measures (metrics) of the North Atlantic ocean state:

1. Meridional Volume Transport (MVT),

2. Meridional Heat Transport (MHT),
3. Spatially-averaged Sea Surface Temperature (SST),
4. Spatially-averaged Ocean Heat Content (OHC).

In general, the first two measures are nonlinear since the location of the measurements depends on the state of the system. However, they can still be used within the linear framework as long as MVT and MHT perturbations are evaluated at fixed locations where their climatological values are maximum (at $z_{\max(\overline{\text{MVT}})}=1500$ m deep and $y_{\max(\overline{\text{MVT}})}=50^\circ\text{N}$ for MVT and at $y_{\max(\overline{\text{MHT}})}=25^\circ\text{N}$ for MHT).

Thus, we can express anomalies in all of these four measures as linear functions of the state vector anomaly, $\langle \mathbf{F}|\mathbf{u} \rangle$, where $\langle \mathbf{F}|$ is an appropriate linear operator. Subsequently, $\langle \mathbf{F}|\mathbf{u} \rangle$ will be the cost function of the optimization procedure:

$$\langle \mathbf{F}|\mathbf{u} \rangle = \begin{cases} \text{MVT} = \int_{z_{\max(\overline{\text{MVT}})}}^0 \int_{x_W}^{x_E} v|_{y_{\max(\overline{\text{MVT}})}} dx dz, \\ \text{MHT} = \iint_{\Sigma} (\bar{v}T + v\bar{T})|_{y_{\max(\overline{\text{MHT}})}} d\sigma, \\ \text{SST} = \frac{1}{S_{\text{NA}}} \iint_{\text{NA}} T|_{z=0} ds, \\ \text{OHC} = \frac{1}{V_{\text{NA}}} \iiint_{\text{NA}} T dv, \end{cases} \quad (2.4)$$

where $\bar{T}$ and T are the trajectory and anomalous temperature and v and $\bar{v}$ and $-$ the trajectory and anomalous meridional component of velocity, respectively; x , y and z are the zonal, meridional and vertical coordinates, x_W and x_E – the specified zonal coordinates of the western and eastern basin boundaries, dv – a volume element, ds – a surface element of the ocean surface, $d\sigma$ – a surface element of a meridional section; S_{NA} is the total surface area of the North Atlantic, V_{NA} – the total volume of the North Atlantic basin, Σ – the total area of a meridional section, NA indicates that the integral is restricted to the northern North Atlantic (*i.e.* from 30°N to 70°N).

To analyze initial perturbations in temperature and salinity (rather than velocity), we need to reduce our parameter space. To that end, we define a projector $\mathbf{P}$ that connects the subspace of temperature and salinity to the full state vector as $|\mathbf{u}\rangle = \mathbf{P}|\mathbf{v}\rangle$, where $|\mathbf{v}\rangle$ represents a thermohaline vector. We also define two norms for these vectors in terms of their effect on density:

$$\langle \mathbf{u}|\mathbf{S}|\mathbf{u} \rangle = \langle \mathbf{v}|\mathbf{P}^\dagger \mathbf{S} \mathbf{P}|\mathbf{v} \rangle = \langle \mathbf{v}|\mathbf{N}|\mathbf{v} \rangle = \frac{1}{V} \iiint (\alpha^2 T^2 + \beta^2 S^2) dv, \quad (2.5)$$

where V is the ocean basin volume, T and S are temperature and salinity components of the full state vector, α is the thermal expansion coefficient, β is the haline contraction coefficient, $\mathbf{S}$ is a norm operator defined in the full state vector space, and $\mathbf{N}$ is the corresponding norm operator defined in the subspaces of temperature and salinity. These norms describe the model departure from the mean annual trajectory in terms of density (averaged over the basin).

Finally, we define a Lagrangian function as:

$$\mathcal{L}(\langle \mathbf{u}(t_i) \rangle, \gamma) = \langle \mathbf{F} | \mathbf{u}(t_m) \rangle - \gamma (\langle \mathbf{u}(t_i) | \mathbf{S} | \mathbf{u}(t_i) \rangle - \epsilon^2), \quad (2.6)$$

where t_i is the initial time (when the optimal initial perturbation is applied), t_m is the maximization time (when the cost function reaches its maximum), and γ is a Lagrange multiplier. ϵ is a parameter associated with the normalization constraint:

$$\langle \mathbf{u}(t_i) | \mathbf{S} | \mathbf{u}(t_i) \rangle = \epsilon^2. \quad (2.7)$$

That is, ϵ measures the magnitude of the initial perturbation (set to $\epsilon/\alpha=1$ mK). Thus, the goal here is to maximize the cost function subject to this normalization constraint. From expression (3.20) and the optimization condition $d\mathcal{L}=0$ the optimal initial perturbations are computed as

$$|\mathbf{u}_{\{t_i, t_m\}}^{\text{opt}}(t_i)\rangle = \pm \epsilon \frac{\mathbf{P}\mathbf{N}^{-1}\mathbf{P}^\dagger\mathbf{M}^\dagger(t_i, t_m)|\mathbf{F}\rangle}{\sqrt{\langle \mathbf{F} | \mathbf{M}(t_m, t_i) \mathbf{P}\mathbf{N}^{-1}\mathbf{P}^\dagger\mathbf{M}^\dagger(t_i, t_m) | \mathbf{F} \rangle}}. \quad (2.8)$$

This expression gives a full explicit solution of the optimization problem, here referred to as the Linear Optimal Perturbation (LOP). In general, LOPs depend both on the initial time t_i and the maximization time t_m . In this study we set t_m to the end of the year (31st of December) and vary t_i . It turns out that the seasonal dependence of this solution is rather weak, which allows us to concentrate solely on decadal timescales. Consequently, we can define the time delay $\tau=t_i-t_m$ (<0) as one of the key parameters of the problem (which by definition of the LOP gives the duration of the transient growth in the system). Note that the seasonal cycle in the model is still important since it ensures an accurate representation of the mean state of the ocean.

To test the impacts of the model surface boundary conditions, two types of surface conditions are used to compute the LOPs – the mixed boundary conditions (MBC) and the flux boundary conditions (FBC). The former apply surface temperature restoring and constant in time freshwater fluxes for salinity. The latter maintain constant surface heat and freshwater fluxes. MBC allow a feedback between oceanic and atmospheric temperatures, but assumes that the atmospheric heat reservoir is infinite. FBC neglect any feedbacks. Realistic ocean-atmosphere interactions generate surface forcing for the ocean that lies probably somewhere in between of these two extreme boundary conditions. Note that the annual trajectory remains identical for both set of experiments, and modifying surface boundary conditions affects only the tangent and adjoint simulations. We also remind the reader that using constant or even time varying surface fluxes in the linearized problem means surface fluxes that are identically zero as long as the surface forcing is independent of ocean state variables.

As mentioned in the introduction, another common method to obtain optimal perturbations is based on the SVD (*e.g.* Farrell and Ioannou, 1996a). Applying our approach (an optimization procedure using Lagrange multipliers), but maximizing a quadratic norm instead of a linear measure of the AMOC would lead to an eigenvalue problem whose solutions are singular vectors of the problem as shown in Sévellec et al. (2007). (A similar

result has been independently obtained in the context of atmospheric modes of variability by Vimont, 2010 and Martinez-Villabos and Vimont, 2016.) In the present and previous studies we choose to maximize linear measures for two main reasons. Firstly, as discussed before, in a linear framework changes in MVT, MHT, SST and OHC are conveniently expressed by linear functions of the state vector. Secondly, using linear measures yields an explicit solution of the problem, (3.12), which eliminates the necessity to solve an eigenvalue problem with much higher computational costs. A more extensive discussion of this point can be found in Sévellec et al. (2007).

2.4.2 Results

To check the existence of the most optimal (*i.e.* most effective) delay we have compared the impacts of the optimal perturbations of each measure in a range of τ from 0 to 1,000 yr. Following (3.12), we have

$$\langle \mathbf{F} | \mathbf{u}_\tau^{\text{opt}}(0) \rangle = \langle \mathbf{F} | \mathbf{M}(-\tau) | \mathbf{u}_\tau^{\text{opt}}(\tau) \rangle = \pm \epsilon \sqrt{\langle \mathbf{F} | \mathbf{M}(-\tau) \mathbf{P} \mathbf{N}^{-1} \mathbf{P}^\dagger \mathbf{M}^\dagger(\tau) | \mathbf{F} \rangle}. \quad (2.9)$$

Using this diagnostic reveals striking differences in the system sensitivity of different measures (Fig. 2.2). Whereas OHC has an optimal transient timescale of one decade (more exactly -9.9 yr), MVT and MHT do not. The almost monotonically decreasing sensitivity of MVT and MHT to optimal initial perturbations as a function of time delay (Fig. 2.2a and b) suggests that MVT and MHT can be modified by nearly instantaneous perturbations (with just a few weeks or months delay) much more efficiently than by perturbations in the distant past. In contrast, OHC shows the highest sensitivity to perturbations applied a decade earlier (Fig. 2.2d).

Examining the SST sensitivity to optimal perturbations reveals two local maxima (Fig. 2.2c) – one for zero delay and another for a delay in the interannual range (-5.8 yr). The zero-delay maximum in sensitivity corresponds to the trivial result of a spatially uniform surface temperature anomaly in the North Atlantic with no subsurface signature. Such sensitivity disappears for delays longer than one month is disregarded here. Consequently, in the rest of this study we will consider only the ~ 6 yr maximum in the SST sensitivity. For all four measures used, the impacts of initial perturbations are greater under fixed boundary conditions (FBC) than under mixed boundary conditions (MBC) as the surface temperature restoring limits the impact of surface temperature anomalies (solid *vs.* dashed lines in Fig. 2.2). Indeed, since by construction LOPs avoid inefficient contributions, the temperature signature of LOPs for MBC is close to zero at the ocean surface, which weakens the overall impacts of optimal perturbations for this type of boundary conditions. The differences between FBC and MBC become more pronounced when the spatially-averaged SST is used as the measure, because this particular variable is directly affected by the choice of surface boundary conditions for temperature (Fig. 2.2c). In contrast, for measures such as to MVT and MHT, the results corresponding to different boundary conditions start diverging only after one decade. This suggests that the impacts of initial perturbations (except for SST) are relatively insensitive to the choice of surface boundary conditions, especially since the maximum sensitivity emerges within the first decade.

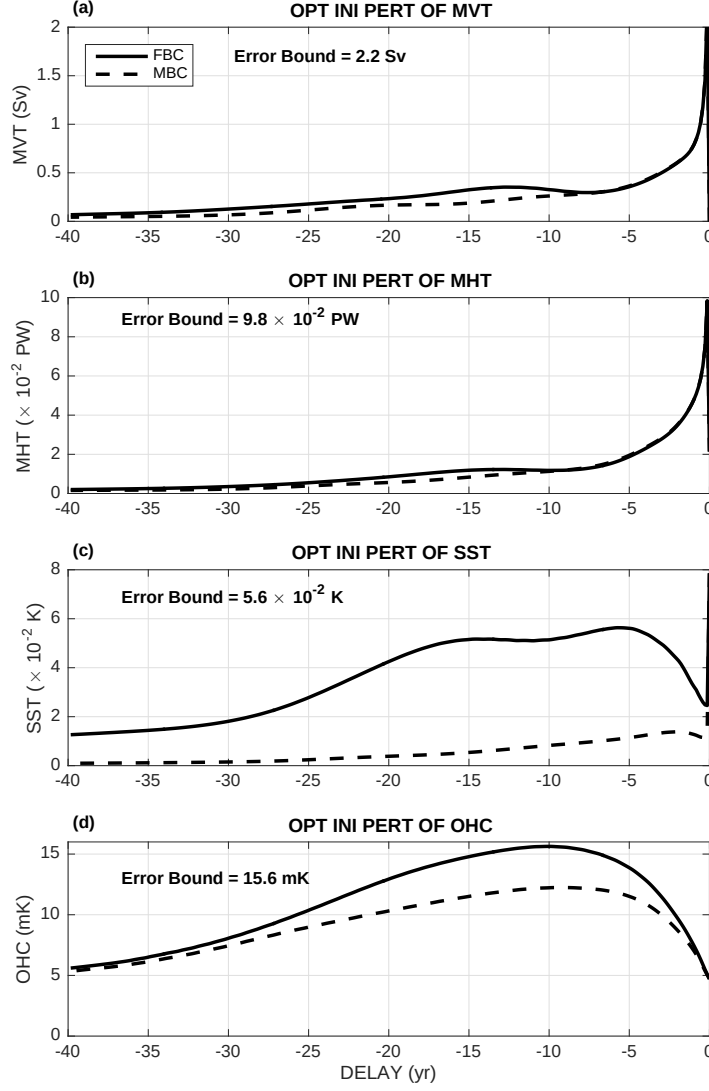


Figure 2.2: (a-d) The impact of the optimal thermohaline perturbations of MVT, MHT, SST, and OHC on the respective variables as a function of the time delay τ . The impact is defined as the maximum magnitude that a particular variable would reach at the peak of the transient growth. Solid and dashed lines represent that MVT and MHT are affected most efficiently by near instantaneous perturbations ($\tau \simeq 0$), whereas OHC and SST are most sensitive to past perturbations. The choice of the boundary conditions is most important for SST. Hereafter, in Figs. 2.2-2.7 and 2.9-2.12, the magnitude of the initial perturbations given by the norm is scaled to the order of 1 mK (*i.e.* $\alpha^{-1} \sqrt{\langle \mathbf{u}(0) | \mathbf{S} | \mathbf{u}(0) \rangle} = 10^{-3}$ K). In the context of ocean predictability, the error bound is defined as the maximum impact of a particular initial perturbation with this magnitude across all tested delays for FBC (instantaneous values are disregarded for SST, see the text).

Considering the spatial structure of the optimal initial perturbations with the most efficient delay reveals striking differences in the horizontal length scale of the perturbations, especially in the zonal direction. Whereas the optimal perturbations of OHC and SST are basin-scale anomalies (Figs. 2.3 and 2.4), the perturbations of MVT and MHT (with a 3-month delay for example) are coastally-trapped anomalies extending along the eastern and western boundaries of the North Atlantic and positioned close to the latitudes where these two variables are measured in the model, *i.e.* 50°N and 25°N (Figs. 2.5 and 2.6). To understand these differences we will now focus on MVT and OHC (since MHT and SST behave qualitatively similar to the former and the latter, respectively).

For MVT, the optimal perturbations combine temperature and salinity anomalies that constructively modify the density field (*i.e.* cold anomalies are accompanied by higher salinity). The induced density pattern is positive in the West of the basin and negative in the East, with virtually no signature in the interior (Fig. 2.5). The resulting density contrast across the basin induces an East-West baroclinic pressure difference that has to be balanced by a zonally-averaged meridional geostrophic flow. Following Hirschi et al. (2003), $v \propto \partial_x P$, we have $\bar{v} \propto (P_{\text{West}} - P_{\text{st}})$, where v ($\bar{v}$) is the (zonally-averaged) meridional velocity, P – pressure, x – the zonal direction, and P_{East} and P_{West} indicate pressure at the eastern and western boundaries of the basin, respectively. This flow alters MVT and MHT, which corresponds to the strengthening of the meridional overturning circulation. Since coastal ocean adjustment occurs significantly faster than the decadal timescale, this perturbation induces MVT and MHT changes almost instantaneously.

In contrast, the optimal perturbations of OHC combine temperature and salinity anomalies localized in the northwestern part of the North Atlantic basin adjacent to Canada, Greenland and Iceland. These anomalies penetrate below the thermocline, reaching the maximum slightly below the thermocline (at $\sim 1,200$ m) and persisting in the deep ocean (Fig. 2.3). These initial perturbations, when scaled to 1 mK, lead after 9.9 yr to an OHC anomaly of +12.6 mK. Stronger perturbations would lead to a proportionally stronger change in OHC.

The mechanism of the transient growth allowing such amplification of initial anomalies in the North Atlantic on decadal timescales has been previously identified by Sévellec and Fedorov (2015a). They demonstrated that a positive surface density anomaly along the north-western boundary of the North Atlantic, either a cooling or an increase of salinity or both, should lead to the strengthening of the AMOC after ~ 9 yr. They also showed that the density anomaly has to reach the deep ocean, penetrating below the thermocline, to be particularly efficient (Sévellec and Fedorov, 2013b, 2015a). The resulting strengthening of the AMOC is due to the efficient stimulation of large-scale baroclinic (thermal) Rossby waves, which induce an oscillation between MVT and OHC. This oscillation has a roughly 24 yr period and involves changes in MVT and OHC that are in quadrature ($\text{MVT} > 0 \rightarrow \text{OHC} > 0 \rightarrow \text{MVT} < 0 \rightarrow \text{OHC} < 0 \dots$, Sévellec and Fedorov, 2013a). Because of the different spatial scales of the optimal perturbations for OHC and MVT, the ocean response to these initial disturbances differs with time as well. Following (3.12), one can obtain a simple expression that describes the temporal evolution of any of the

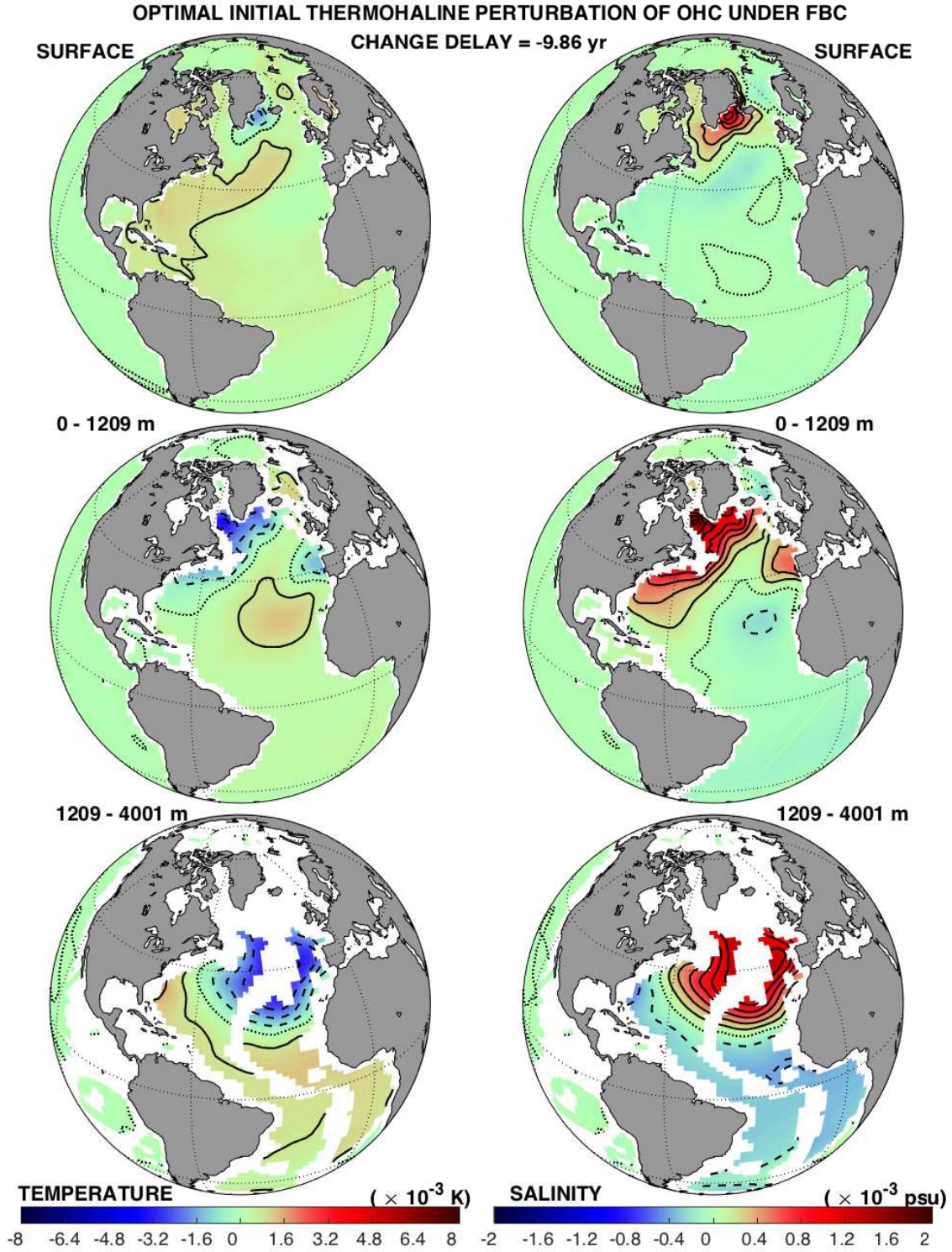


Figure 2.3: The structure of the optimal initial thermohaline perturbation having the strongest impact on OHC after an optimal delay of 9.9 yr (*i.e.* the most efficient delay in Fig. 2.2d). This perturbation has an initial OHC anomaly on the order of -1 mK, but induces anomaly of $+15.6$ mK after 9.9 yr. Note that temperature and salinity have a constructive (additive) effects on the initial density perturbation. The results are for the flux boundary conditions (FBC).

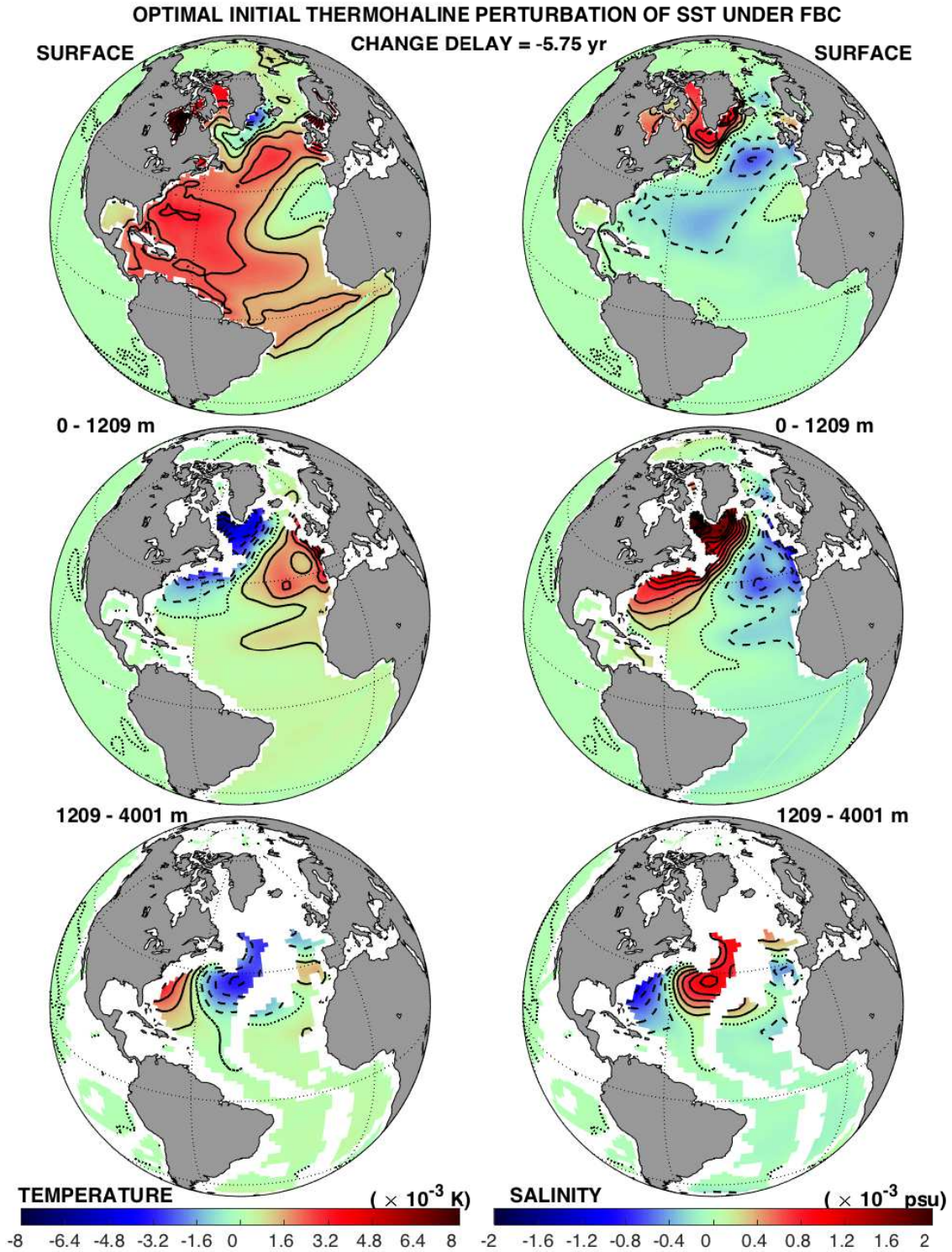


Figure 2.4: As in Fig. 2.3 but for the optimal perturbation of spatially-averaged SST and for an optimal delay of 5.8 yr (*i.e.* the most efficient delay in Fig. 2.2c). This perturbation has an initial anomaly in SST on the order of +1 mK, but induces anomaly of +56 mK after 5.8 yr. The results are for the flux boundary conditions (FBC).

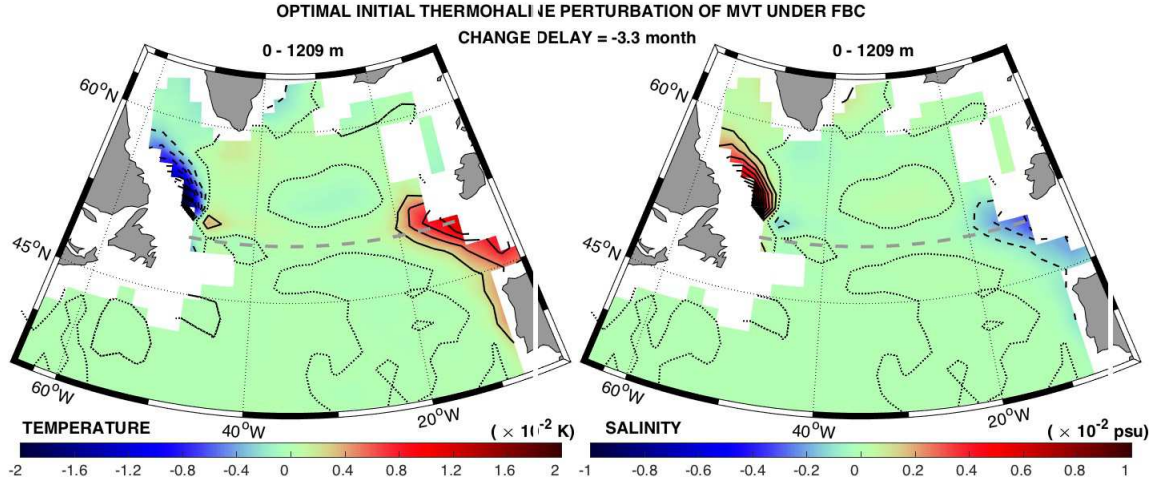


Figure 2.5: The upper-ocean structure of the optimal thermohaline perturbation that has the largest impact on MVT after a delay of 3.3 months. Temperature and salinity are averaged between 0 and 1209 m. The light gray dashed line indicates the latitude at which MVT is estimated. Note the two coastally trapped waves located on the opposite sides of the basin – at time zero they will cross this latitude, leading to a large east-west density gradient and hence a net meridional geostrophic flow. The results are for the flux boundary conditions (FBC).

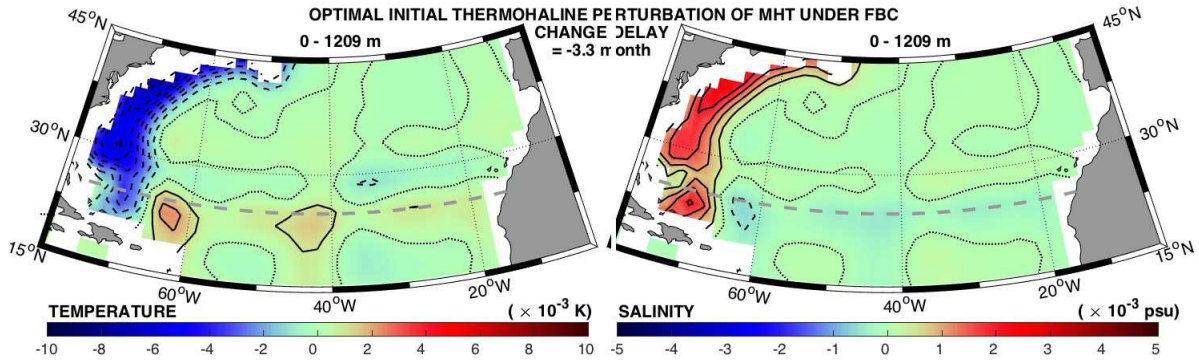


Figure 2.6: As in Fig. 2.5 but for the optimal perturbation of MHT, also corresponding to a 3.3-month delay. The light gray dashed line indicates the latitude at which MHT is estimated. Note the coastally trapped wave on the western side of the basin that will cross this latitude at time zero. The results are for the flux boundary conditions (FBC).

four variables after the initial disturbance is applied (at $t=0$):

$$\langle \mathbf{F} | \mathbf{u}_\tau^{\text{opt}}(t) \rangle = \langle \mathbf{F} | \mathbf{M}(t) | \mathbf{u}_\tau^{\text{opt}}(0) \rangle. \quad (2.10)$$

As expected, we find that each climate variable experiences the strongest increase when the system is perturbed by the LOPs computed for this particular variable (Fig. 2.7). However, MVT changes caused by its optimal perturbations are strongly damped just after a few years, whereas OHC variations caused by its respective perturbations are only weakly damped (Figs. 2.7a and d). LOPs computed for one variable still perturb other variables. For example, the optimal perturbations of OHC lead to variations in MVT. These variations occur as a result of the excitation of the interdecadal oscillatory mode discussed in above (Sévellec and Fedorov, 2013a). Because of their large spatial scales, the optimal perturbations of OHC are more efficient for stimulating this mode.

The ocean response to the optimal perturbations of SST is generally similar to that of OHC, but the transient growth lasts a shorter time, and the oscillatory nature of the response is perhaps more noticeable (Fig. 2.7c). Like MVT, MHT shows a strongly damped response to its optimal perturbations (Fig. 2.7b), as the initial density anomalies have virtually no signature in the ocean interior that could support the signal on longer timescales.

2.5 Idealized model

2.5.1 Idealized model formulation

So far we have demonstrated that MVT and OHC (or MHT and SST) exhibit dramatic differences in terms of sensitivity to the initial perturbations – meridional volume and heat transports are most sensitive to shorter timescales associated with smaller spatial scale anomalies located near the basin western and eastern boundaries, whereas the two spatially-averaged temperature variables are most sensitive to basin-scale anomalies which can induce transient growth up to a decade long. To further investigate the role of the horizontal length scale of the anomalies, specifically in controlling the timescale and maximum sensitivity for each of the four climatic variables, we use an idealized model of linear ocean dynamics formulated for the North Atlantic. The setting of the model (Fig. 2.8) is similar to that of Sévellec and Fedorov (2013a), Sévellec and Fedorov (2015a), and Sévellec and Huck (2015), and the text below follows these studies with minor modifications.

The idealized model describes the linear dynamics of the ocean GCM with several approximations applied. For simplicity, we neglect the seasonal cycle and consider the system autonomous. Also, the large spatial scale of the problem allows us to reduce the momentum equations to geostrophic balance on a β -plane (the planetary-geostrophic regime or the geostrophic regime of type 2, see Phillips, 1963; Colin de Verdière, 1988; Salmon, 1998)

The model treats anomalies in temperature T' and salinity S' on two ocean levels – the top level (of depth h) and the deep level (of depth $\tilde{h}$). These anomalies are chosen to

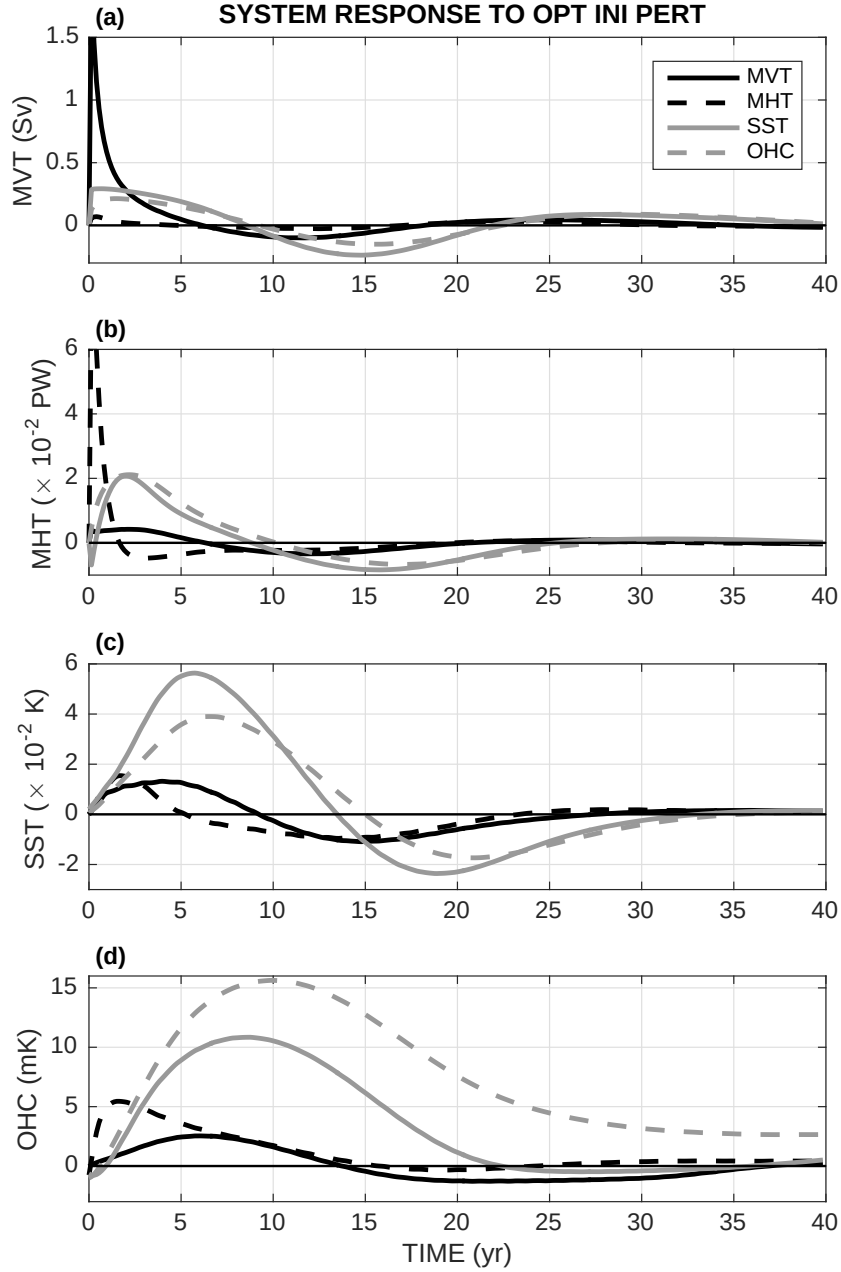


Figure 2.7: The evolution of (a) MVT, (b) MHT, (c) SST, and (d) OHC in response to the optimal initial thermohaline perturbations specifically calculated for MVT (black solid line), MHT (black dashed line), SST (gray solid line) or OHC (gray dashed line). The spatial structure of the imposed initial temperature and salinity fields was shown in Fig. 2.5, 2.6, 2.4, and 2.3, respectively. Note the strongly damped oscillatory-like behavior with periodicity of about 24 years that occurs in many of these computations; it is related to the leading, interdecadal eigenmode of the system (Sévellec and Fedorov, 2013a).

be functions of time t and the zonal coordinate x , and their evolution follows a set of advection-diffusion equations. To simplify the mathematical procedure of the analysis, meridional variations in T' and S' are neglected. The zonal extent of the model basin is W ; its full depth is H (numerical values of these and other parameters are given in Tab. 2.1).

The equations are linearized with respect to the mean state of the ocean. In particular, at the upper level we impose the mean zonal flow $\bar{u}$ and the mean temperature and salinity gradients. These gradients have meridional and vertical components: $\partial_y\{\bar{T}, \bar{S}\}$ and $\partial_z\{\bar{T}, \bar{S}\}$, where y and z are the meridional and vertical coordinates, and $\bar{T}$ and $\bar{S}$ are mean temperature and salinity, respectively. These gradients in the equations are approximated by simple constants obtained from the GCM output. In the deep ocean those constants are set to zero. Mean zonal gradients of temperature and salinity are neglected.

Table 2.1: Parameters of the idealized model.

h	1200 m	model top level thickness
H	4500 m	total ocean depth
W	60°	basin zonal size
L	60°	basin meridional size
κ	$2 \times 10^3 \text{ m}^2 \text{ s}^{-1}$	horizontal tracer diffusivity
g	9.8 m s^{-2}	acceleration due to gravity
f	10^{-4} s^{-1}	Coriolis parameter
β_f	$1.5 \times 10^{-11} \text{ m}^{-1} \text{ s}^{-1}$	latitudinal gradient of the Coriolis parameter (<i>i.e.</i> planetary vorticity gradient)
α	$2 \times 10^{-4} \text{ K}^{-1}$	thermal expansion coefficient
β	$7 \times 10^{-4} \text{ psu}^{-1}$	haline contraction coefficient
ΔT	-15 K	mean meridional temperature contrast
ΔS	-1.5 psu	mean meridional salinity contrast
$\bar{u}$	$2.5 \times 10^{-2} \text{ m s}^{-1}$	mean zonal velocity in the upper ocean

For the prognostic variables of the model, we choose T'_u and S'_u , and T'_d and S'_d – temperature and salinity anomalies in the upper and deep oceans, respectively. These variables evolve according to the linearized advective-diffusion equations with horizontal diffusivity κ (see the Appendix). The system is closed using thermal wind balance with a baroclinicity condition for the meridional velocity, a linear equation of state for seawater, a continuity equation, and the rigid-lid approximation.

The last step is to apply the Fourier transform along the zonal direction to T'_u , T'_d , S'_u and S'_d , which yields, after some algebra, equations for the corresponding Fourier coefficients T'^u_{cn} , T'^d_{sn} , T'^u_{cn} , T'^d_{sn} , S'^u_{cn} , S'^d_{sn} , S'^u_{cn} , and S'^d_{sn} , where n indicates the wave number, u and d stand for the upper and deep model levels, and c and s - for cosine and sine. These equations are summarized in the Appendix and used in the analysis below. As shown by Sévellec and Fedorov (2013a) and Sévellec and Fedorov (2015a), this idealized model is

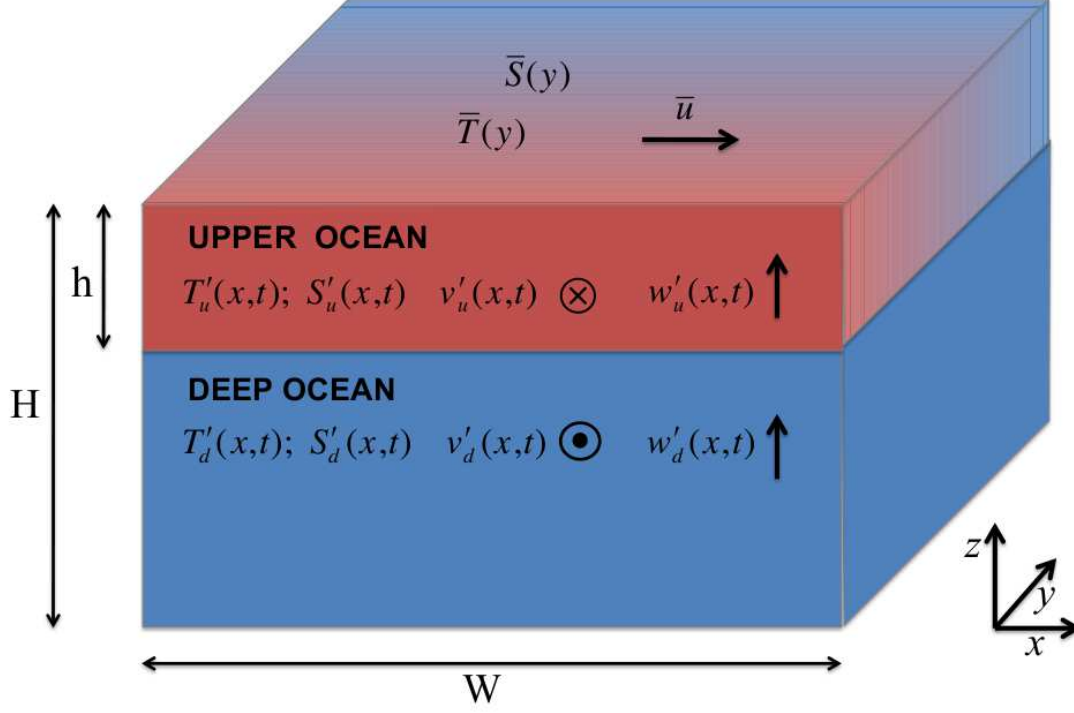


Figure 2.8: A schematic of the idealized model. The two levels of the model represent the upper and deep ocean. The prognostic variables are temperature and salinity at each level (T'_u , S'_u , T'_d , and S'_d , respectively). The four diagnostic variables are meridional and vertical velocities, also at each level (v'_u , w'_u , v'_d , and w'_d). The model free parameters are the upper-ocean thickness h , the total ocean depth H , the zonal extent of the Atlantic basin W , the mean meridional flow $\bar{u}$, and the mean temperature and salinity fields ($\bar{T}$ and $\bar{S}$). For $\bar{T}$ and $\bar{S}$ we choose linear functions of y at the top level (both fields decreasing with latitude) and constants at the deeper level. Those constants are equal to the values of temperature and salinity in the upper ocean at the northern boundary of the basin. We also assume a nonzero vertical stratification in the upper layer that can support baroclinic Rossby waves due to the β -effect. The dependence of the model variables on spatial coordinates (zonal - x , meridional - y , and vertical - z) and time t is shown in brackets. Color (blue to red) represents mean temperature variations (colder to warmer). A similar idealized model was used in Sévellec and Fedorov (2013a), Sévellec and Fedorov (2015a), and Sévellec and Huck (2015).

able to reproduce the dynamical behavior of the linear tangent and adjoint versions of the ocean GCM with the flux boundary conditions. Those authors have also discussed the boundary conditions at the basin western and eastern boundaries required for such a model (restricting n to odd numbers).

Using this idealized spectral model we apply a similar optimization procedure as applied in section 2.4. For simplicity, here we will focus only on MVT and OHC, which show the highest sensitivity to small-scale instantaneous anomalies and basin-scale decadal anomalies, respectively.

2.5.2 Idealized model results

To investigate the role of the horizontal length scale of the optimal perturbations, especially their zonal scale, we have computed the LOPs of the idealized model for different values of N (from 1 to 20, where N is the number of the retained Fourier terms). Decreasing N is equivalent to applying a low-pass filter along the zonal direction, filtering smaller-scale anomalies. A Fourier series truncated at $N=20$ would resolve roughly 3° of longitude (approaching the resolution of the ocean GCM).

First, let us consider the impacts of the optimal perturbations when we retain these first 20 Fourier terms in the expansion. In this case, the idealized model reproduces the delayed sensitivity of the full GCM very closely – OHC is most sensitive to initial perturbations after a roughly 10-year delay, while MVT is sensitive to instantaneous perturbations (Fig. 2.9). Next, we compute LOPs but retain only the first Fourier term ($N=1$, corresponding to the basin zonal length scale). Our computations reveal a striking difference – whereas the optimal perturbations of OHC are almost not affected by the filtering, the optimal perturbations of MVT show a much reduced sensitivity for instantaneous perturbations. In fact, the largest sensitivity is now for a 10-year delay (Fig. 2.9, dashed line). This comparison of the filtered versus unfiltered computations confirms that OHC is primarily affected by large-scale anomalies whereas MVT is affected by all scales, including the smallest zonal scale in the model.

This particular behavior can be further analyzed by looking at the formulation of the cost function in the spectral model:

$$\begin{aligned} \text{MVT} &= \sum_{n=1}^{2N+1} \frac{gh\tilde{h}}{fH} \left[h(-\alpha T'_{cn} + \beta S'_{cn}) + \tilde{h}(-\alpha T'^d_{cn} + \beta S'^d_{cn}) \right], \\ \text{OHC} &= \sum_{n=1}^{2N+1} \frac{2}{n\pi H} \left(hT'_{sn} + \tilde{h}T'^d_{sn} \right). \end{aligned}$$

Whereas MVT is independent of the wavenumber n , OHC is inversely proportional to it. This means that potentially each Fourier mode has similar impacts on MVT, increasing its overall sensitivity to perturbations. At short times, when smaller-scale anomalies are not yet damped by horizontal diffusion, it is the cumulative effect of all spatial scales that controls MVT anomalies, which makes instantaneous values of MVT virtually unpredictable. On the other hand, OHC is inversely proportional to the wave number, with smaller sensitivity to high wave numbers (*i.e.* small-scale anomalies). This fundamental difference between MVT and OHC comes from the fact that the former depends of

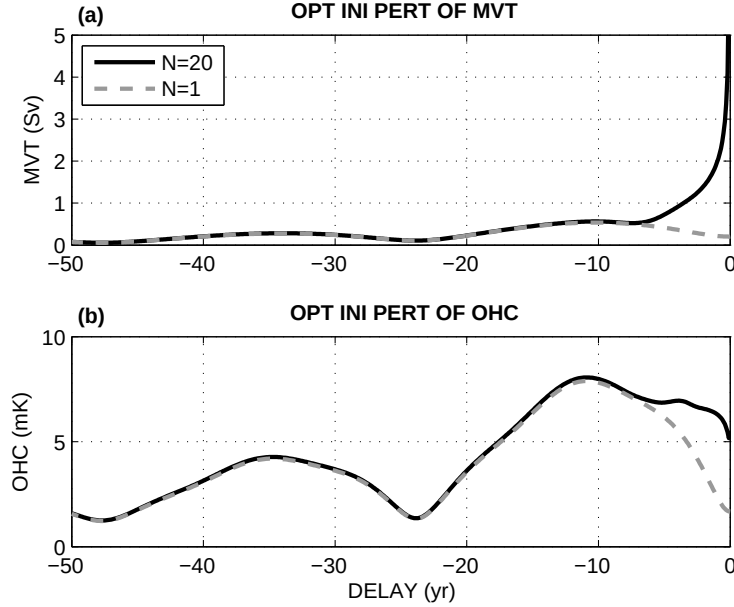


Figure 2.9: The impact of the optimal initial perturbations of MVT and OHC on the respective variables as a function of the time delay τ , as obtained from the idealized model (*cf.* Fig. 2.2 for the ocean GCM). The impact is defined as the maximum magnitude that a particular variable would reach at the peak of the transient growth. Solid and dashed lines show results retaining twenty Fourier modes ($N=20$; equivalent to a 3° zonal resolution) or just one ($N=1$; the basin scale). Note that MTV is affected most efficiently by near instantaneous perturbations ($\tau \simeq 0$); however, to capture this feature, one has to retain a sufficient number of Fourier modes. In contrast, OHC is most sensitive to past perturbations ($\tau \simeq -10$ yr), which remains true even if one severely truncates the Fourier expansion.

the east-west temperature difference (assuming geostrophic balance, $\text{MVT} \propto \int_{\text{East}}^{\text{West}} v' dx \propto \rho_{\text{West}} - \rho_{\text{East}}$, where v' is the anomalous meridional flow, x is the zonal coordinate, and ρ_{East} and ρ_{West} are density anomalies at the eastern and western boundaries, respectively). In contrast, the latter is an integral of temperature ($\text{OHC} \propto \int_{\text{East}}^{\text{West}} T' dx$), which filters out small-scale sensitivity. Thus, MVT is more sensitive to smaller scales than OHC. Thus, only if one restricts consideration to basin-scale anomalies, MVT and OHC behave similarly (dashed gray lines in Fig. 2.9). In that case, LOPs of both variables induce optimal transient change on a decadal timescale, following the mechanism discussed in Sévellec and Fedorov (2013b) and Sévellec and Fedorov (2015a). This transient change corresponds to the non-normal stimulation of a 24 yr oscillatory eigenmode (Sévellec and Fedorov, 2013a), whose signature is evident for example in the oscillatory-like variations in sensitivity in Fig. 2.9.

2.6 Implications for predictability of the ocean state

We now return to the results of the ocean GCM and examine their implications for the predictability of the ocean state in the North Atlantic described in terms of the four climate variables under consideration. In fact, whether an optimal delay exists or not has direct consequences for the predictability of the system. Since optimal initial anomalies with an average magnitude of just a few mK (in the norm sense) are able to significantly modify the chosen ocean state metrics, the optimal time delays for each particular metric sets a potential time limit on its predictability. Note that the maximum values of these initial anomalies remain below 10^{-2} K, far below the accuracy of ocean measurements. In this sense, SST and OHC are predictable up to 6 and 10 yr, respectively, but instantaneous values of MVT and MHT are unpredictable (as errors projecting on the optimal perturbations can impact the latter variables almost immediately).

To further quantify the system predictability, we compare the maximum impact of the initial perturbations (scaled to 1 mK) to the typical magnitude of variability of each metric in a full climate GCM. Accordingly, we define the Normalized Error Bound as the ratio between the former and the latter. The coupled model we use is IPSL-CM5, which employs the same ocean model with the same configuration (Marti et al., 2010) as the present study.

Following (3.13), the Error Bound, *i.e.* the maximum impact of an optimal perturbation on a particular measure, can be computed as $\max_{\tau} (\epsilon \sqrt{\langle \mathbf{F} | \mathbf{M}(-\tau) \mathbf{P} \mathbf{N}^{-1} \mathbf{P}^{\dagger} \mathbf{M}^{\dagger}(\tau) | \mathbf{F} \rangle})$, with $\epsilon/\alpha = 10^{-3}$ K (Tab. 2.2). The magnitude of variability of each measure can be estimated as the standard deviation of its annual-mean value from a 1,000 yr long preindustrial simulation of the IPSL model (Dufresne et al., 2013; Mignot and Bony, 2013). The ratio of the Error Bound to the standard deviation yields the Normalized Error Bound.

We obtain that the Normalized Error Bound exceeds 100% for MVT and MHT but stays below 40% for SST and OHC. Such strong relative impacts of small disturbances (1 mK) compared to the overall variability confirm lower predictability of MVT and MHT. For OHC the Normalized Error Bound reaches only 34%, suggesting higher predictability.

The effect on these results of changing the type of surface boundary conditions is small (Tab. 2.2). However, one should keep in mind that these numbers are important only in a relative sense, since the initial disturbances could be scaled by an arbitrary factor. Another critical factor relevant to these results is the extent to which the spatial structure of the noise actually present in the ocean model or in nature would project onto the optimal perturbations.

For SST, variability in the climate model is strongly affected by atmospheric processes, absent in the forced context, which could artificially reduce the Normalized Error Bound. Keeping in mind this limitation, our result suggest that small disturbances in the ocean model can lead to an SST change comparable to the overall SST variability in the climate model (*i.e.* 4 mK anomaly leading to a Normalized Error Bound of nearly 100% for the flux boundary conditions).

Table 2.2: Characteristics of the most efficient transient change for optimal initial perturbations corresponding to different measures and scaled to the order of 1 mK (*i.e.* $\alpha^{-1}\sqrt{\langle \mathbf{u}(0)|\mathbf{S}|\mathbf{u}(0)\rangle}=10^{-3}$ K). Values in bold indicate experiments with the strongest impact. Climatic Error Bounds are defined after applying a 30-year averaging to the relevant variables.

Optimization measure	Boundary conditions	Most efficient time delay	Absolute Error Bound	Normalized Error Bound	Absolute Climatic Error Bound	Normalized Climatic Error Bound
MVT	FBC	≥ -0.1 yr	± 2.2 Sv	128%	± 0.36 Sv	61%
	MBC	≥ -0.1 yr	± 2.2 Sv	128%	± 0.30 Sv	51%
MHT	FBC	≥ -0.1 yr	$\pm 9.8 \times 10^{-2}$ PW	144%	$\pm 1.5 \times 10^{-2}$ PW	71%
	MBC	≥ -0.1 yr	$\pm 9.8 \times 10^{-2}$ PW	144%	$\pm 1.4 \times 10^{-2}$ PW	64%
SST	FBC	-5.8 yr	$\pm 5.6 \times 10^{-2}$ K	24%	$\pm 4.4 \times 10^{-2}$ K	45%
	MBC	≥ -0.1 yr	$\pm 1.5 \times 10^{-2}$ K	6.4%	$\pm 1.0 \times 10^{-2}$ K	9%
OHC	FBC	-9.9 yr	± 15.6 mK	34%	± 12.6 mK	42%
	MBC	-9.4 yr	± 12.2 mK	26%	± 10.4 mK	35%

Thus far, the cost function has been defined using instantaneous measurements. However, for climatic purposes one would like to predict a time average of each metric rather than its instantaneous value. To test how time averaging would modify the system sensitivity to small disturbances and hence its predictability, we now compute the Error Bound for a time-averaged cost function:

$$\langle \mathbf{F} | \mathbf{u} \rangle = \begin{cases} \langle \text{MVT} \rangle_{\Pi} = \int_{t_m - \Pi}^{t_m} \int_{z_{\max}(\overline{\text{MVT}})}^0 \int_{x_W}^{x_E} v |y_{\max(\overline{\text{MVT}})} dx dz dt, \\ \langle \text{MHT} \rangle_{\Pi} = \int_{t_m - \Pi}^{t_m} \iint_{\Sigma} v T |y_{\max(\overline{\text{MHT}})} d\sigma dt, \\ \langle \text{SST} \rangle_{\Pi} = \int_{t_m - \Pi}^{t_m} \frac{1}{S_{\text{NA}}} \iint_{\text{NA}} T|_{z=0} ds dt, \\ \langle \text{OHC} \rangle_{\Pi} = \int_{t_m - \Pi}^{t_m} \frac{1}{V_{\text{NA}}} \iiint_{\text{NA}} T dv dt, \end{cases} \quad (2.11)$$

where Π is the length of the time averaging interval (we use Π in the range 1 to 40 yr). As in the previous analysis, the effect of averaging strongly differs for MVT and MHT *vs* SST and OHC (Fig. 2.10). For the former metrics, as the length of the time averaging increases the influence of LOPs decreases, suggesting a better predictability. However, for

the latter metrics, the time averaging does not affect the impacts of LOPs much, so that their predictability does not change.

We now define the Climatic Error Bound as the maximum impact of a LOP on a 30-year average of a particular metric. The choice of $\Pi=30$ yr is somewhat arbitrary, corresponding to a traditional definition of “climate”. Going from the Error Bound to the Climatic Error Bound shows a dramatic decrease in the impact of LOPs by a factor of 5 for MVT and MHT, but no significant change for SST and OHC (Tab. 2.2).

To further assess the relative impact of small disturbances, for each metric we compare the Error Bound computed for different time averages with their standard deviation in the IPSL model also computed using different durations of the running average. As previously, we estimate the ratio of the two and define the Normalized Climatic Error Bound (Fig. 2.11). For MVT and MHT, the Normalized Error Bound shows an overall decrease for longer averaging intervals, leading to the values of the Normalized Climatic Error Bound (defined for $\Pi=30$ yr) at 60% and 70%, respectively. For MVT there exists a best averaging interval of about 10 yr with a Normalized Climatic Error Bound of 50%, suggesting a “sweet spot” for MVT predictability. For MHT, the longer the averaging interval is, the better.

For OHC, the results are only weakly dependent on the duration of the averaging, except for a weak local maximum (*i.e.* a worst case in terms of prediction) around 20 yr. The Normalized Climatic Error Bound is about 40%. Overall, both MVT and MHT seem to become more predictable when a long time-average is used, whereas OHC predictability changes very little (Fig. 2.11d). For SST, different types of surface boundary conditions produce rather different results (Fig. 2.11c), suggesting that this issue should be considered in a fully coupled model.

2.7 Discussion

The climate system exhibits variability on timescales ranging from synoptic to interannual and decadal to centennial and much longer (Ghil, 2002). These different timescales modulate one another; for example, the activity of tropical cyclones is modulated on decadal timescales by the Atlantic Multidecadal Variability (Goldenberg et al., 2001; Delworth and Mann, 2000). Thus, to predict changes in weather pattern or the occurrence of extreme events, we need to improve our ability to predict decadal climate variations.

On such decadal timescales, model initial conditions are critical for prediction (*vs.* a particular CO₂ emission scenario more relevant on centennial timescale, Hawkins and Sutton, 2009b). However, since the climate system is chaotic, any errors in the estimate of these initial conditions can lead in time to significant errors in both the phase and amplitude of the signal, following the same principle as the well-known “butterfly effect” for the atmosphere (Lorenz, 1963).

To that end, here we have determined the timescale and intensity of the transient growth of initial disturbances of the North Atlantic ocean state within a forced ocean model framework. The next question is how fast and how strongly these initial errors can modify

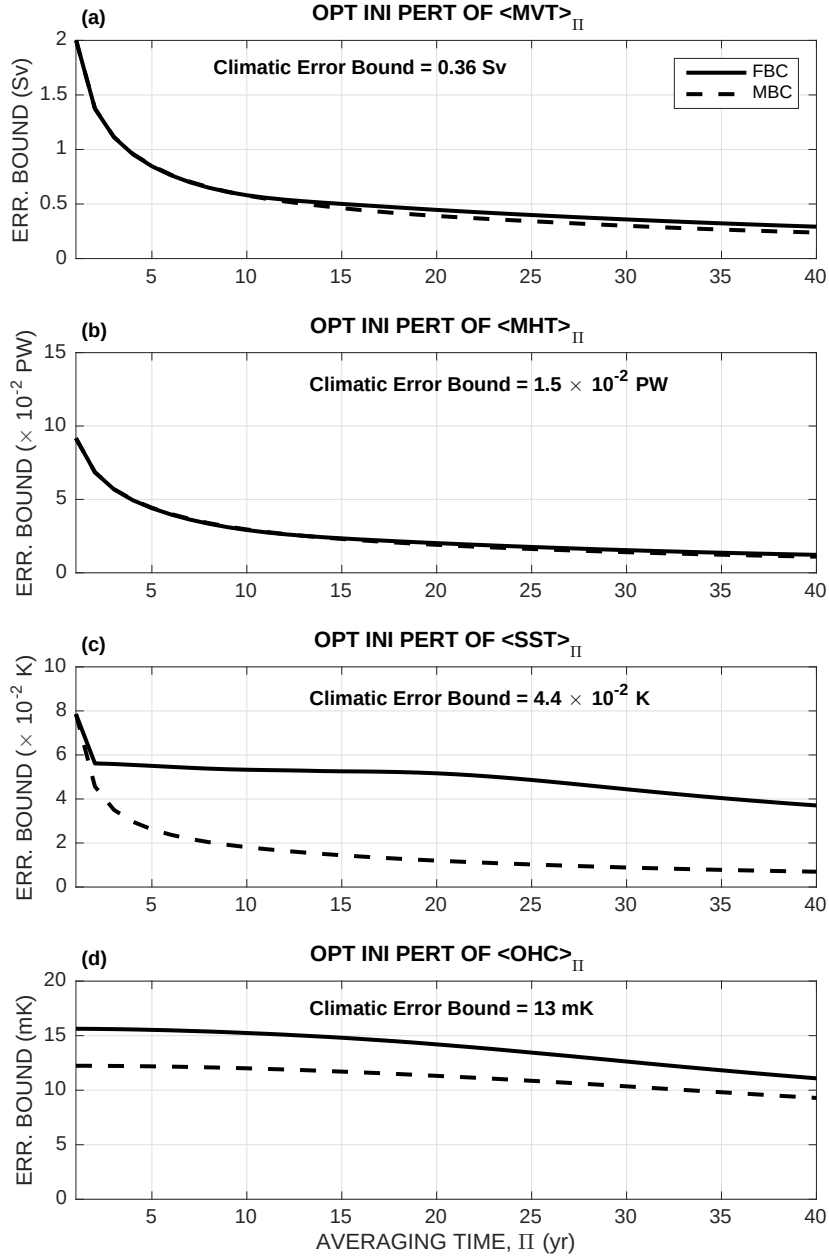


Figure 2.10: (a-d) Error Bound (*i.e.* the maximum impact of the respective optimal initial perturbation) as a function of the averaging time Π applied to: MVT, MHT, SST, and OHC. These averaged variables are denoted as $\langle \text{MVT} \rangle_{\Pi}$, for example. Solid and dashed lines represent different boundary conditions (FBC and MBC, respectively). For $\Pi=0$ the values of Error Bound would be the same as the maximum values in Fig. 2.2. The Climatic Error Bound is defined as the Error Bound for time averages with $\Pi=30$ yr.

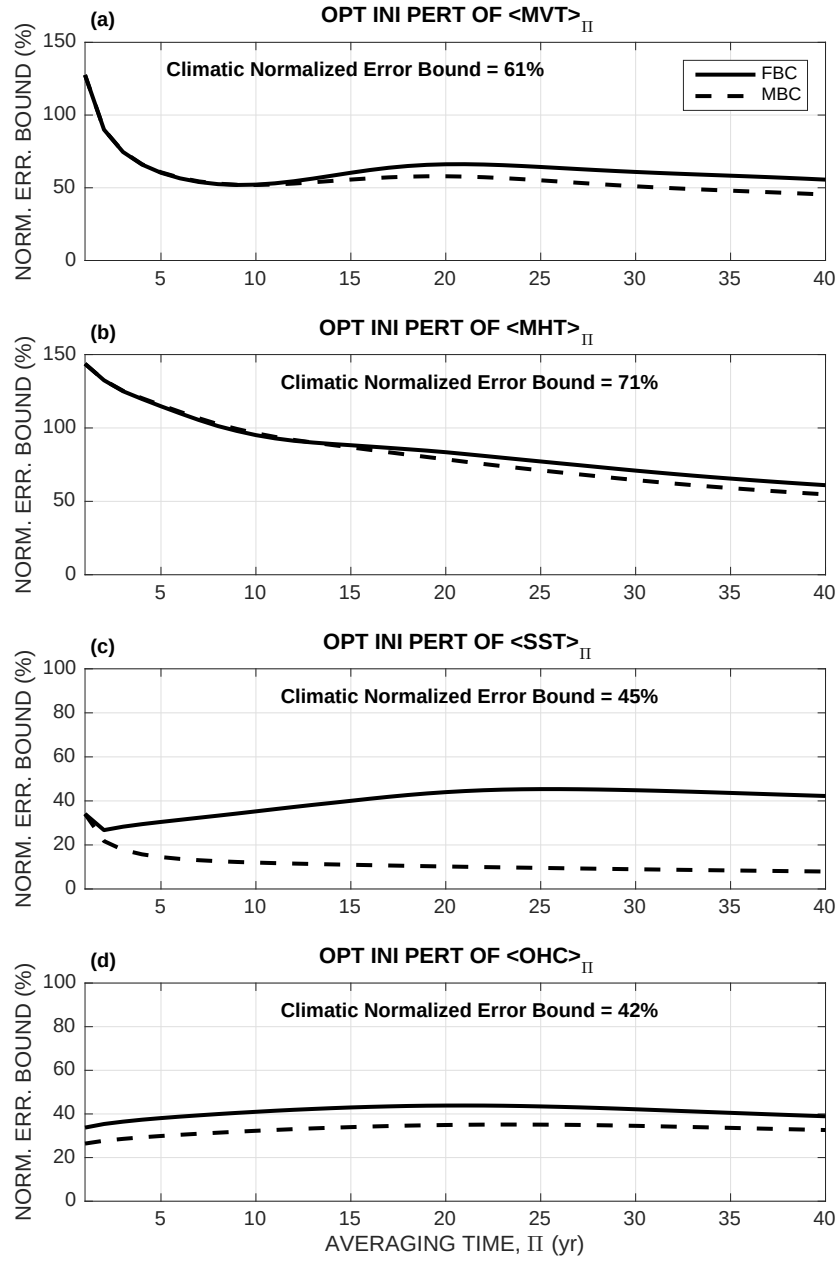


Figure 2.11: As in Fig. 2.10 but normalized with the standard deviation of time averages of each variable in a fully coupled model (IPSL-CM5). The Climatic Normalized Error Bound is defined as the Normalized Error Bound for time averages with $\Pi=30$ yr.

the ocean state, thus setting a limit on ocean predictability. Answering this question, we have assessed the sensitivity to initial conditions of four metrics of the North Atlantic ocean state: meridional volume transport (MVT at 50°N and 1,500 m depth), meridional heat transport (MHT at 25°N), sea surface temperature (SST averaged between 30°N and 70°N), and ocean heat content (OHC averaged between 30°N and 70°N and with depths). We have followed the Generalized Stability Analysis (Farrell and Ioannou, 1996a,b), but reshaped it for the purpose of looking at linear measures of the ocean state, as suggested by Sévellec et al. (2007). This method involves the computation of LOPs (Linear Optimal Perturbations) obtained by maximizing a Lagrangian function, which requires the use of an adjoint to the ocean GCM (Sévellec and Fedorov, 2015a).

We have demonstrated that ocean predictability strongly depends on the metrics chosen to evaluate the ocean state. For instance metrics corresponding to large spatial scales, such as the spatially-averaged ocean heat content and SST, have predictability of 10 and 6 yr, respectively. On the other hand, instantaneous values of meridional volume and heat transports, which can be strongly influenced by processes at the boundaries of the basin, do not show any predictability. We have rationalized this result using an idealized ocean model.

These findings are generally consistent with the 7.5 yr optimal transient growth for the AMOC intensity obtained by Zanna et al. (2011) in an ocean model using an idealized configuration (a rectangular basin with flat bottom). However, those authors applied a different metric for the AMOC volume transport by averaging the stream function meridionally and vertically. Such spatial averaging filters out the effect of small-scale disturbances. Hence, their metric becomes more comparable to our SST and OHC metrics (also based on spatial averages). As discussed in our study, the averaging leads to a higher sensitivity to past disturbances than to instantaneous disturbances.

In our study, we have shown that the ocean predictability is indeed controlled by the transient growth of small perturbations. These perturbations can grow significantly, so that the characteristic timescale of the transient growth sets the limit of predictability of the system. A complementary analysis (Sévellec and Fedorov, 2013b) demonstrated that the transient growth timescale is given by the damping timescale due to horizontal diffusion limiting the residence timescale of deep ocean perturbations. This damping affects differently perturbations having small and large spatial scales, as expected from the Laplace operator of diffusion ($\tau \propto \lambda^2$, where τ is the diffusive timescale and λ is the spatial scale of the perturbation). Thus, the metrics influenced by perturbations with smaller spatial scales (*e.g.* MVT and MHT) have a shorter predictability, whereas metrics predominantly influenced by large-scale anomalies (*e.g.* SST and OHC) can have longer predictability. Since small spatial scales in the ocean are given by the internal Rossby radius of deformation, in principle this makes instantaneous values of MVT and MHT unpredictable. In contrast, the largest spatial scale being the basin size implies longer predictability for SST and OHC limited by a potential predictability barrier at roughly 6 and 10 yr, respectively. For SST however this result might change in a coupled ocean-atmosphere context due to the competing effects of active ocean-atmosphere coupling, if any is present, and atmospheric stochastic noise.

In general, applying time averaging to the metrics enhances their predictability in comparison to their instantaneous values. It is especially true for MVT and MHT, for which time averaging filters out dependency on small-scale perturbations and increases predictability by more than a factor of 4 (in terms of error growth) when these two metrics are averaged over 30 yr.

Nevertheless, when compared to variability in a climate model (*i.e.* IPSL-CM5, Dufresne et al., 2013; Mignot and Bony, 2013), all 30-year averaged metrics show a relatively weak predictability (despite a local optimal for MVT for the averaging interval of 10 years). Indeed, initial perturbations of only 1 mK can lead on decadal timescale to anomalies reaching roughly 60% and 40% of the MVT and OHC standard deviation, respectively. Whether this result makes these variables unpredictable in practice, in view of the typical uncertainty of temperature measurements, depends on the extent to which errors in the initial conditions would project onto the optimal perturbations.

In addition, we find that, regardless of the surface boundary conditions used, the four climate metrics under consideration have sensitivity to initial perturbations in the deep ocean (below 2,000 m) as large as that to initial perturbations in the upper ocean (in the top 2,000 m), see Fig. 2.12. This finding, consistent with the previous results of Sévellec and Fedorov (2013b), stresses the need for accurate measurements in the deep ocean below the normal depth limit of ARGO floats.

To test the robustness of our results we have compared the impacts of two different types of surface boundary conditions for the ocean model: the mixed and flux boundary conditions (the former use a restoring term for temperature). We find that, except for the SST metric, the results are only weakly modified by the choice of the boundary conditions. This gives us more confidence in our results for the MVT, MHT and OHC metrics. However, the results for SST do depend on the boundary conditions, which implies that ocean-atmosphere coupling can become a defining factor for this metric. The SST metric is arguably the most important for climate prediction, since it directly influences surface air temperature.

By construction, our forced ocean framework disregards potential effects of large-scale active ocean-atmosphere coupling (passive coupling is included in the mixed boundary conditions) and stochastic noise linked to atmospheric synoptic variability. Whereas the former can be a source of predictability, the latter contributes to error growth. Thus, in the future we intend to extend our analysis to a fully coupled ocean-atmosphere context. Note however that the results of our ongoing work on testing the LOPs of North Atlantic ocean heat content in a coupled GCM do suggest that the general development in the first two decades still follows closely the predictions of the linear, ocean-only computations with a modified surface temperature damping coefficient as long as the imposed initial perturbations are relatively small, *e.g.* comparable to the coupled model internal variability (? , to be submitted).

Finally, while the results of this study have been obtained by linearizing the primitive equations around the model climatological basic state, it could be useful to test their robustness using a more variable model background state. This can be done by computing the model trajectory using surface boundary conditions based on historical observations

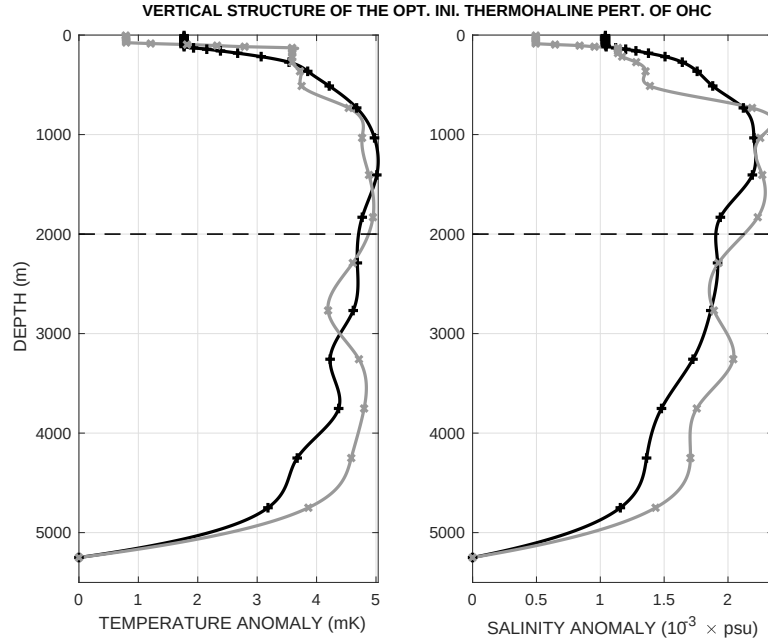


Figure 2.12: The vertical structure and magnitude of the optimal initial perturbations for OHC under FBC (thick black lines, full structure shown in Fig. 2.3) and MBC (thick gray lines) as a function of depth. Crosses indicate the maximum values of (left) temperature and (right) salinity anomalies at each level of the ocean GCM and are connected by a cubic spline interpolation. The horizontal dashed line indicates the typical depth limit of Argo floats (2,000 m). In effect, this plot shows the sensitivity of North Atlantic ocean heat content to past disturbances at different depths. The strongest sensitivity develops for disturbances located at a depth between 1,000 m and 2,000 m. The net system sensitivity associated with the deep ocean (below 2,000 m) is comparable if not greater than that associated with the upper ocean (above 2,000 m). Note that the relative differences in sensitivity for different surface boundary conditions (FBC and MBC) become small below several hundred meters.

(versus the climatological forcing in the present study). Also, the results of this study could be extended to a fully nonlinear framework. Specifically, Conditional Nonlinear Optimal Perturbations (Mu and Zhang, 2006; Zu et al., 2013; Li et al., 2014) provide a natural extension of the LOPs. Together with considering the effects of ocean-atmosphere coupling, these ideas will offer directions for future work.

Acknowledgment. This research was supported by grants from DOE Office of Science (DE-SC0007037), National Science Foundation (AGS-1405272) and from Natural and Environmental Research Council UK (MESO-CLIP, NE/K005928/1 and SMURPHS, NE/N005767/1). Support from the Yale University High Performance Computing facilities is also acknowledged. We thank Brian Dobbins for his help with setting up numerical experiments.

Appendix 2: Details of the idealized model

2.7.1 Equations

We describe here the idealized model used in section 2.5 in more detail. The setting of the model follows that of Sévellec and Fedorov (2013a), Sévellec and Fedorov (2015a), and Sévellec and Huck (2015), and is provided here for completeness. However, whereas Sévellec and Fedorov (2013a) investigated the existence and properties of the least-damped, interdecadal AMOC eigenmode and how this mode can be excited most efficiently, here we focus on how initial disturbances can affect different measures of the North Atlantic ocean state, following more closely Sévellec and Fedorov (2015a). This problem deals with transient behavior of the system and requires a specific approach in view of the system nonnormality.

As discussed in section 2.5, for the prognostic variables of the 2-layer model, we choose T'_u and S'_u , and T'_d and S'_d – temperature and salinity anomalies in the upper and deep oceans, respectively. These variables evolve according to linearized advective-diffusion equations with horizontal diffusivity κ :

$$\partial_t T'_u = -\bar{u}\partial_x T'_u - v'_u\partial_y \bar{T} - w'_u\partial_z \bar{T} + \partial_x (\kappa\partial_x T'_u), \quad (2.12a)$$

$$\partial_t S'_u = -\bar{u}\partial_x S'_u - v'_u\partial_y \bar{S} - w'_u\partial_z \bar{S} + \partial_x (\kappa\partial_x S'_u), \quad (2.12b)$$

$$\partial_t T'_d = \partial_x (\kappa\partial_x T'_d), \quad (2.12c)$$

$$\partial_t S'_d = \partial_x (\kappa\partial_x S'_d), \quad (2.12d)$$

where v'_u and w'_u are the meridional and vertical velocities in the upper ocean.

The system is closed using thermal wind balance with a baroclinicity condition for the meridional velocity, a linear equation of state for seawater, a continuity equation, and the rigid-lid approximation:

$$\partial_z v' = \frac{g}{f} (\alpha\partial_x T' - \beta\partial_x S'), \quad (2.13a)$$

$$\int_{-H}^0 v' dz = 0, \quad (2.13b)$$

$$\partial_y v' + \partial_z w' = 0, \text{ with } w'|_{z=0} = 0 \quad (2.13c)$$

where v' and w' are the meridional and vertical velocities; both are functions of x , y and z . f is the Coriolis parameter, g - the acceleration of gravity, α - the thermal expansion coefficient, β - the haline contraction coefficient (the numerical values of these parameters are given in Table 2.1). To obtain the meridional and vertical velocity at the upper level, we vertically discretize the latter set of equations on the upper and deep levels using the Arakawa C-grid (together with simple linear interpolations between the missing values, if needed).

Using the Fourier coefficients with respect to x , we express temperature and salinity anomalies as

$$\begin{aligned} T'_{\{u,d\}} &= \sum_n T'_{cn}^{\{u,d\}} \cos\left(\frac{n\pi}{W}x\right) + T'_{sn}^{\{u,d\}} \sin\left(\frac{n\pi}{W}x\right), \\ S'_{\{u,d\}} &= \sum_n S'_{cn}^{\{u,d\}} \cos\left(\frac{n\pi}{W}x\right) + S'_{sn}^{\{u,d\}} \sin\left(\frac{n\pi}{W}x\right). \end{aligned}$$

We apply this Fourier transform with respect to x to the set of equations (2.12); using (2.13) reduces the idealized model to

$$d_t |\mathbf{u}_{id}\rangle = \mathbf{A}_{id} |\mathbf{u}_{id}\rangle, \quad (2.14)$$

with

$$\langle \mathbf{u}_{id} | = (T'_{cn}{}^u, T'_{sn}{}^u, T'_{cn}{}^d, T'_{sn}{}^d, S'_{cn}{}^u, S'_{sn}{}^u, S'_{cn}{}^d, S'_{sn}{}^d),$$

and

$$\mathbf{A}_{id} = \begin{pmatrix} -\kappa \left(\frac{n\pi}{W}\right)^2 & A_{1,2} - \frac{n\pi}{W}\bar{u} & 0 & A_{1,4} & 0 & A_{1,6} & 0 & A_{1,8} \\ A_{2,1} + \frac{n\pi}{W}\bar{u} & -\kappa \left(\frac{n\pi}{W}\right)^2 & A_{2,3} & 0 & A_{2,5} & 0 & A_{2,7} & 0 \\ 0 & 0 & -\kappa \left(\frac{n\pi}{W}\right)^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\kappa \left(\frac{n\pi}{W}\right)^2 & 0 & 0 & 0 & 0 \\ 0 & A_{5,2} & 0 & A_{5,4} & -\kappa \left(\frac{n\pi}{W}\right)^2 & A_{5,6} + \frac{n\pi}{W}\bar{u} & 0 & A_{5,8} \\ A_{6,1} & 0 & A_{6,3} & 0 & A_{6,5} - \frac{n\pi}{W}\bar{u} & -\kappa \left(\frac{n\pi}{W}\right)^2 & A_{6,7} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -\kappa \left(\frac{n\pi}{W}\right)^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\kappa \left(\frac{n\pi}{W}\right)^2 \end{pmatrix},$$

where $T'_{cn}{}^u$, $T'_{sn}{}^u$, $T'_{cn}{}^d$, $T'_{sn}{}^d$, $S'_{cn}{}^u$, $S'_{sn}{}^u$, $S'_{cn}{}^d$ and $S'_{sn}{}^d$ are the Fourier coefficients, $|\mathbf{u}_{id}\rangle$ is the state vector, and $\mathbf{A}_{id}$ is the Jacobian Matrix of the idealized model. Here, n ($= 1, 3, 5, \dots$) indicates the wave number, u and d stand for the upper and deep levels, and c and s - for cosine and sine. The nonzero terms in this matrix correspond to diffusion, advection by the mean flow, geostrophic self-advection, and the baroclinic Rossby wave propagation. The terms describing the two latter effects are calculated as

$$\begin{aligned}
A_{1,2} = -A_{2,1} = \frac{h}{\tilde{h}} A_{1,4} = -\frac{h}{\tilde{h}} A_{2,3} &= -\frac{n\pi}{W} \left(\frac{\alpha g \tilde{h} h}{2Hf} \partial_y \bar{T} - \frac{\alpha g \tilde{h} h^2 \beta_f}{4Hf^2} \partial_z \bar{T} \right), \\
A_{1,6} = -A_{2,5} = \frac{h}{\tilde{h}} A_{1,8} = -\frac{h}{\tilde{h}} A_{2,7} &= +\frac{n\pi}{W} \left(\frac{\beta g \tilde{h} h}{2Hf} \partial_y \bar{T} - \frac{\beta g \tilde{h} h^2 \beta_f}{4Hf^2} \partial_z \bar{T} \right), \\
A_{5,6} = -A_{6,5} = \frac{h}{\tilde{h}} A_{5,8} = -\frac{h}{\tilde{h}} A_{6,7} &= +\frac{n\pi}{W} \left(\frac{\beta g \tilde{h} h}{2Hf} \partial_y \bar{S} - \frac{\beta g \tilde{h} h^2 \beta_f}{4Hf^2} \partial_z \bar{S} \right), \\
A_{5,2} = -A_{6,1} = \frac{h}{\tilde{h}} A_{5,4} = -\frac{h}{\tilde{h}} A_{6,3} &= -\frac{n\pi}{W} \left(\frac{\alpha g \tilde{h} h}{2Hf} \partial_y \bar{S} - \frac{\alpha g \tilde{h} h^2 \beta_f}{4Hf^2} \partial_z \bar{S} \right),
\end{aligned}$$

where $\tilde{h}=H-h$ is the thickness of the deep level, and $\beta_f=d_y f$ is the meridional gradient of the Coriolis parameter estimated for the northern Atlantic (between 30°N and 60°N).

2.7.2 Optimization

To understand the transient behavior of the idealized model, we now perform a generalized stability analysis following the procedure outlined in section 2.4.1 To that end, we need to define (i) the measure of the optimization problem or the cost function, and (ii) an appropriate norm for the initial anomalies, both in the context of the idealized model Accordingly, we define the operator $\langle \mathbf{F}_{id} |$ for MVT and OHC as

$$\langle \mathbf{F}_{id} | = \begin{cases} \sum_{n=1}^{2N+1} \frac{gh\tilde{h}}{fH} \left(-\alpha h, 0, -\alpha \tilde{h}, 0, \beta h, 0, \beta \tilde{h}, 0 \right) & \text{for MVT, and} \\ \sum_{n=1}^{2N+1} \frac{2}{n\pi H} \left(0, h, 0, \tilde{h}, 0, 0, 0, 0 \right) & \text{for OHC.} \end{cases}$$

The norm, $\mathbf{S}_{id}$, is chosen as

$$\begin{aligned}
\langle \mathbf{u}_{id} | \mathbf{S}_{id} | \mathbf{u}_{id} \rangle &= \frac{h}{H} \left(\alpha^2 T_{cn}^{u^2} + \alpha^2 T_{sn}^{u^2} + \beta^2 S_{cn}^{u^2} + \beta^2 S_{sn}^{u^2} \right) \\
&\quad + \frac{\tilde{h}}{H} \left(\alpha^2 T_{cn}^{d^2} + \alpha^2 T_{sn}^{d^2} + \beta^2 S_{sn}^{d^2} + \beta^2 S_{sn}^{d^2} \right). \quad (2.15)
\end{aligned}$$

To test the role of the horizontal scales for the solution, we solve the optimization problem truncating the Fourier expansion using different total number of waves ($N=1$, and $N=20$). $N=20$ corresponds to a 3-degree resolution, close to the GCM resolution used in this study. $N=1$ can describe only the basin scale. The results of the optimization analysis are discussed in section 2.5.

Chapter 3

Dynamical Attribution of Prediction Uncertainty

This work was done in collaboration with H. A. Dijkstra, S. S. Drijhout, and A. Germe.

3.1 Summary

In this chapter, the relation between two approaches to assess the ocean predictability on interannual to decadal time scales is investigated. The first pragmatic approach consists of sampling the initial condition uncertainty and assess the predictability through the divergence of this ensemble in time. The second approach is provided by a theoretical framework to determine error growth by estimating optimal linear growing modes. In this paper, it is shown that under the assumption of linearized dynamics and normal distributions of the uncertainty, the exact quantitative spread of ensemble can be determined from the theoretical framework. This spread is at least an order of magnitude less expensive to compute than the approximate solution given by the pragmatic approach. This result is applied to a state-of-the-art Ocean General Circulation Model to assess the predictability in the North Atlantic of four typical oceanic metrics: the strength of the Atlantic Meridional Overturning Circulation (AMOC), the intensity of its heat transport, the two-dimensional spatially-averaged Sea Surface Temperature (SST) over the North Atlantic, and the three-dimensional spatially-averaged temperature in the North Atlantic. For all tested metrics, except for SST, $\sim 75\%$ of the total uncertainty on interannual time scales can be attributed to oceanic initial condition uncertainty rather than atmospheric stochastic forcing. The theoretical method also provide the sensitivity pattern to the initial condition uncertainty, allowing for targeted measurements to improve the skill of the prediction. It is suggested that a relatively small fleet of several autonomous underwater vehicles can reduce the uncertainty in AMOC strength prediction by 70% for 1-5 years lead times.

3.2 Introduction

Anthropogenic global warming has changed Earth's climate over the last century (IPCC, 2007, 2013). In this context, there is an ever increasing societal pressure to predict (as accurately as possible) climate changes from local to global scales and from seasonal to centennial time scales. Previous studies have suggested that on interannual to decadal time scales internal variability dominates the uncertainty in global temperature changes, whereas on multidecadal to centennial time scales the emission scenarios are more important (Hawkins and Sutton, 2009b; Branstator and Teng, 2012b; IPCC, 2013). Because of its slow variability and its large heat content, the ocean can control climate variations on interannual to decadal time scales. For example, variability of the Atlantic Meridional Overturning Circulation (AMOC) can suppress anthropogenically forced warming in the North Atlantic (Drijfhout, 2015). Hence predicting AMOC variations, and more generally the North Atlantic Ocean state is crucial for accurate climate predictions on interannual to decadal time scales. Moreover, because of its robust quasi-harmonic multi-decadal variation (Kushnir, 1994; Frankcombe and Dijkstra, 2009; Chylek et al., 2011), the North Atlantic is a perfect candidate for successful interannual to decadal climate prediction (Griffies and Bryan, 1997).

Considering the chaotic nature of several components of the climate system, in particular the atmosphere (Lorenz, 1963), a pragmatic approach has been widely used to determine climate predictability on different time scales (Hurrell et al., 2006; Meehl et al., 2009). This approach consists of acknowledging the uncertainty in initial conditions by taking an ensemble of nearby initial conditions and evaluating the predictability by computing the time evolution of the spread of this ensemble (e.g., Boer, 2011). There are various strategies to accurately sample the initial condition uncertainty and to accurately define the ensemble (e.g., Persechino et al., 2013). However, except for a few dedicated studies (e.g., Du et al., 2012; Baehr and Piontek, 2014; Germe et al., 2017b), the role of the oceanic uncertainties has often been overlooked in these ensemble design strategies, despite being a possible source of predictability (Hawkins et al., 2016).

Since the early work of Griffies and Bryan (1997), there has been a large body of work suggesting the predictability on interannual to decadal time scales of climatically relevant metrics of the North Atlantic Ocean, such as the AMOC (Collins and Sinha, 2003; Pohlmann et al., 2004; Collins et al., 2006; Latif et al., 2006; Keenlyside et al., 2008; Msadek et al., 2010; Teng et al., 2011). For example, Branstator and Teng (2014) suggested predictability of up to 20 years for one AMOC mode of variability, whereas Hermanson and Sutton (2010) suggested an average predictability of 5 years for the annual AMOC. Although using different methods to assess predictability, these two examples illustrate the difficulty of a robust quantitative estimation of AMOC predictability. Hence, despite good qualitative progress in assessing the interannual to decadal predictability of the North Atlantic climate variability, the quantitative results substantially still differ between studies. This disagreements might be caused by the model uncertainty that has been showed to dominate on decadal time scale (Hawkins and Sutton, 2009b). Beyond this, one other hypothesis to explain the lack of quantitative agreement is the rather small

number of members (~ 10) used to build the ensembles (Sévellec and Sinha, 2017). This number is far from being enough to systematically sample the initial condition uncertainty of the climate system (Deser et al., 2012). Hence another methodology is highly desirable to assess predictability on interannual to decadal time scales.

Generalized Stability Analysis has been developed to estimate the transient growth of small perturbations (GSA; Farrell and Ioannou, 1996a,b) rather than their asymptotic growth, as used in classical Linear Stability Analysis (Strogatz, 1994). This generalization to finite time development makes GSA particularly well suited to study predictability (Palmer, 1999). Hence, in the context of the North Atlantic there has been a wide range of applications with this method, from idealized ocean models to fully coupled ones (Tziperman and Ioannou, 2002; Zanna and Tziperman, 2008; Alexander and Monahan, 2009; Hawkins and Sutton, 2011), and even observations (Zanna, 2012). Sévellec et al. (2007) suggested a subtle but fundamental modification of the GSA: instead of estimating the maximum growth of perturbations through a quadratic norm, one can estimate the maximum change in any linear combination of the state-variables.

This modification simplifies the solution going from an eigenvalues problem (i.e., Singular Value Decomposition, hard to tackle in a state-of-the-art climate model) to an explicit solution (i.e., Linear Optimal Perturbation – LOP, Sévellec et al., 2007). This allowed the study of a wide range of climatically relevant problems of the North Atlantic from idealized ocean models (Sévellec et al., 2007) to state-of-the-art ocean general circulation models (Sévellec and Fedorov, 2017). Also, through this new formulation of GSA, changes are not restricted to non-normal growths and are easily comparable to the pragmatic ensemble approach based on perturbing initial conditions.

These methods are particularly useful to determine regions of sensitivities to ocean initial conditions (Montani et al., 1999; Leutbecher et al., 2002). They have been shown to be extremely efficient in improving typhoon forecasts (Qin and Mu, 2011; Zhou and Mu, 2011), for instance. Hence, in the context of the AMOC, Wunsch (2010) and Heimbach et al. (2011) suggested the use of these methods to assess regions where enhanced sampling strategy can improve prediction. Alternative methods to assess the effect of enhanced sampling strategies have also been proposed, such as initializing different layers of the ocean (Dunstone and Smith, 2010), but these methods are not yet able to determine the most sensitive region with the same level of details.

In this study, the relation between the two approaches is discussed and it is shown that under two assumptions (linearized dynamics and normal distribution of uncertainties), the spread of an ensemble can be retrieved from a theoretical framework. Unlike the ensemble simulation strategy, the theoretical framework provides an exact quantitative estimate of the predictability (measured through the Predictive Power), as it does not depend on the arbitrary number of members like the ensemble method. In section 3.3, we develop the method for a quantitative assessment of the predictability and illustrate the solution using an idealized stochastic model. In section 3.4, we apply the solution to a state-of-the-art ocean General Circulation Model (GCM) for four ocean metrics related to the AMOC. Applications to the design of efficient monitoring systems for climate prediction are given in section 3.5. A discussion on the limits of the methods, conclusions and directions for

future work are included in section 3.6.

3.3 Theory

3.3.1 Propagating errors in a linear framework

Here we discuss the mathematical framework of our method. Readers more interested in its application to the North Atlantic Ocean circulation can skip this section.

The prognostic equations of the full nonlinear ocean model can, after discretization, be written as a general non-autonomous finite-dimensional dynamical system:

$$d_t |\mathbf{U}\rangle = \mathcal{N}(|\mathbf{U}\rangle, t), \quad (3.1)$$

where $\mathcal{N}$ are time-dependent nonlinear terms and the forcing of the model, $|\mathbf{U}\rangle$ is a state vector consisting of all prognostic variables, and t is time. The state vector is comprised of the three dimensional fields of temperature, salinity, and zonal and meridional velocities, together with the two dimensional field of barotropic stream function. Since we study a finite-dimensional vector space, we can also define a dual vector $\langle \mathbf{U}|$ through the Euclidian scalar product $\langle \mathbf{U}|\mathbf{U}\rangle$.

We decompose the state vector as $|\mathbf{U}\rangle = |\bar{\mathbf{U}}\rangle + |\mathbf{u}\rangle$, where $|\bar{\mathbf{U}}\rangle$ is the nonlinear annually varying trajectory (i.e., the climatological background state) and $|\mathbf{u}\rangle$ is a perturbation. Under the assumptions of small perturbations and following Farrell and Ioannou (1996b), the temporal evolution of the perturbation follows a linear equation:

$$d_t |\mathbf{u}\rangle = \mathbf{A}(t) |\mathbf{u}\rangle + |\mathbf{f}^{\text{sto}}(t)\rangle, \quad \mathbf{A}(t) = \left. \frac{\partial \mathcal{N}}{\partial |\mathbf{U}\rangle} \right|_{|\bar{\mathbf{U}}\rangle}, \quad (3.2)$$

where $\mathbf{A}(t)$ is a Jacobian matrix (a function of the trajectory $|\bar{\mathbf{U}}\rangle$) and $|\mathbf{f}^{\text{sto}}(t)\rangle$ is an anomalous stochastic forcing imposed by the atmospheric synoptic noise, now made explicit. We also define an adjoint to the Jacobian matrix $\mathbf{A}^\dagger$ as $\langle \mathbf{a}|\mathbf{A}|\mathbf{b}\rangle = \langle \mathbf{b}|\mathbf{A}^\dagger|\mathbf{a}\rangle$, where $|\mathbf{a}\rangle$ and $|\mathbf{b}\rangle$ are two anomalous state vectors.

We can integrate (3.2) to obtain an explicit expression for the perturbation as a function of time (Farrell and Ioannou, 1996b):

$$|\mathbf{u}(t)\rangle = |\mathbf{u}^{\text{ini}}(t)\rangle + |\mathbf{u}^{\text{sto}}(t)\rangle, \quad (3.3a)$$

$$|\mathbf{u}^{\text{ini}}(t)\rangle = \mathbf{M}(t, t_i) |\mathbf{u}^{\text{ini}}(t_i)\rangle, \quad (3.3b)$$

$$|\mathbf{u}^{\text{sto}}(t)\rangle = \int_{t_i}^t ds \mathbf{M}(t, s) |\mathbf{f}^{\text{sto}}(s)\rangle, \quad (3.3c)$$

where $|\mathbf{u}^{\text{ini}}(t)\rangle$ is the perturbation at time t induced by the initial disturbance at time t_i , such that $|\mathbf{u}(t_i)\rangle = |\mathbf{u}^{\text{ini}}(t_i)\rangle$; $|\mathbf{u}^{\text{sto}}(t)\rangle$ is the perturbation induced by the stochastic forcing; and $\mathbf{M}(t, t_i)$ is called the propagator of the linearized dynamics from the initial time t_i to a time t . In general the propagator does not commute with its adjoint, $\mathbf{M}^\dagger(t_i, t)\mathbf{M}(t, t_i) \neq \mathbf{M}(t, t_i)\mathbf{M}^\dagger(t_i, t)$, in which case the dynamics is said to be non-normal.

3.3.2 Ensemble spread and predictability

To evaluate the ocean state predictability we will focus on physical metrics of the form $\langle \mathbf{F} | \mathbf{u} \rangle$, where $|\mathbf{F}\rangle$ is a vector defining the cost function. The derivation below is adapted from the theoretical framework set by Chang et al. (2004) to fit the specific goals of our analysis.

Hence, according to (3.3), we can also follow the evolution of any metrics through the expression:

$$\langle \mathbf{F} | \mathbf{u}^{\text{ini}}(t) \rangle = \langle \mathbf{F} | \mathbf{M}(t, t_i) | \mathbf{u}^{\text{ini}}(t_i) \rangle = \langle \mathbf{u}^{\text{ini}}(t_i) | \mathbf{M}^\dagger(t_i, t) | \mathbf{F} \rangle, \quad (3.4a)$$

$$\langle \mathbf{F} | \mathbf{u}^{\text{sto}}(t) \rangle = \int_{t_1}^t ds \langle \mathbf{F} | \mathbf{M}(t, s) | \mathbf{f}^{\text{sto}}(s) \rangle = \int_{t_1}^t ds \langle \mathbf{f}^{\text{sto}}(s) | \mathbf{M}^\dagger(s, t) | \mathbf{F} \rangle. \quad (3.4b)$$

We use the variance to evaluate the spread of the ensemble. The independence of initial oceanic disturbances and atmospheric stochastic disturbances suggests that their covariance is weak and can be neglected. Hence, we obtain:

$$\sigma^2(t) \simeq \sigma_{\text{ini}}^2(t) + \sigma_{\text{sto}}^2(t), \quad (3.5)$$

where σ_{ini}^2 and σ_{sto}^2 are the variances induced by a large sets of N initial oceanic disturbances ($|\mathbf{u}_k^{\text{ini}}(t_i)\rangle$) and of corresponding surface atmospheric disturbances ($|\mathbf{f}_k^{\text{sto}}(s)\rangle$), respectively (k being the index of the random realization or of the individual member in the ensemble).

These two variances can be expressed as:

$$\sigma_{\text{ini}}^2(t) = \frac{1}{N} \sum_{k=1}^N \left\{ \langle \mathbf{F} | \mathbf{u}_k^{\text{ini}}(t) \rangle - \left[\sum_{k=1}^N \langle \mathbf{F} | \mathbf{u}_k^{\text{ini}}(t) \rangle \right] \right\}^2 = \frac{1}{N} \sum_{k=1}^N \langle \mathbf{F} | \mathbf{u}_k^{\text{ini}}(t) \rangle^2, \quad (3.6a)$$

$$\sigma_{\text{sto}}^2(t) = \frac{1}{N} \sum_{k=1}^N \left\{ \langle \mathbf{F} | \mathbf{u}_k^{\text{sto}}(t) \rangle - \left[\sum_{k=1}^N \langle \mathbf{F} | \mathbf{u}_k^{\text{sto}}(t) \rangle \right] \right\}^2 = \frac{1}{N} \sum_{k=1}^N \langle \mathbf{F} | \mathbf{u}_k^{\text{sto}}(t) \rangle^2, \quad (3.6b)$$

since $\lim_{N \rightarrow \infty} \sum_{k=1}^N \langle \mathbf{F} | \mathbf{u}_k^{\text{ini}}(t) \rangle = 0$ and $\lim_{N \rightarrow \infty} \sum_{k=1}^N \langle \mathbf{F} | \mathbf{u}_k^{\text{sto}}(t) \rangle = 0$ by definition of the linear framework. Hence the spread of the ensemble is

$$\sigma_{\text{ini}}^2(t) = \frac{1}{N} \sum_{k=1}^N \langle \mathbf{F} | \mathbf{M}(t, t_i) | \mathbf{u}_k^{\text{ini}}(t_i) \rangle^2 = \frac{1}{N} \sum_{k=1}^N \langle \mathbf{u}_k^{\text{ini}}(t_i) | \mathbf{M}^\dagger(t, t_i) | \mathbf{F} \rangle^2. \quad (3.7a)$$

$$\sigma_{\text{sto}}^2(t) = \frac{1}{N} \sum_{k=1}^N \langle \mathbf{F} | \int_{t_i}^t ds \mathbf{M}(t, s) | \mathbf{f}_k^{\text{sto}}(s) \rangle^2 = \frac{1}{N} \sum_{k=1}^N \left[\int_{t_i}^t ds \langle \mathbf{f}_k^{\text{sto}}(s) | \mathbf{M}^\dagger(s, t) | \mathbf{F} \rangle \right]^2. \quad (3.7b)$$

The equations (3.7) suggest that to measure the spread of initial and stochastic disturbances we can either propagate all the N initial and stochastic disturbances and project them onto the cost function or propagate (with the adjoint) the cost function only once

and project it on the N initial and stochastic disturbances. Obviously, the latter is a lot more efficient and will even allow to rebuild the entire probability density function (PDF). Indeed, the application of a moment (here the second moment or variance) is applied as a post-computation diagnostic. Hence, this demonstration can be reproduced for any statistical moment (not only the variance), so that the statistical properties of the oceanic initial condition and atmospheric stochastic forcing uncertainties can be propagated in the same way. Applying this procedure on any statistical moment of the PDF (μ_n^{ini} and μ_n^{sto}), we obtain:

$$\mu_n^{\text{ini}}(t) = \frac{1}{N} \sum_{k=1}^N \langle \mathbf{F} | \mathbf{M}(t, t_i) | \mathbf{u}_k^{\text{ini}}(t_i) \rangle^n = \frac{1}{N} \sum_{k=1}^N \langle \mathbf{u}_k^{\text{ini}}(t_i) | \mathbf{M}^\dagger(t_i, t) | \mathbf{F} \rangle^n. \quad (3.8a)$$

$$\mu_n^{\text{sto}}(t) = \frac{1}{N} \sum_{k=1}^N \langle \mathbf{F} | \int_{t_i}^t ds \mathbf{M}(t, s) | \mathbf{f}_k^{\text{sto}}(s) \rangle^n = \frac{1}{N} \sum_{k=1}^N \left[\int_{t_i}^t ds \langle \mathbf{f}_k^{\text{sto}}(s) | \mathbf{M}^\dagger(s, t) | \mathbf{F} \rangle \right]^n. \quad (3.8b)$$

Coming back to the special case of the variance, and acknowledging that $\langle \mathbf{F} | \mathbf{v} \rangle^2 = \langle \mathbf{F} | \mathbf{v} \rangle \langle \mathbf{v} | \mathbf{F} \rangle$ (where $|\mathbf{v}\rangle$ is any disturbance), (3.7) can be even more efficiently expressed as:

$$\begin{aligned} \sigma_{\text{ini}}^2(t) &= \langle \mathbf{F} | \mathbf{M}(t, t_i) \left[\frac{1}{N} \sum_{k=1}^N |\mathbf{u}_k^{\text{ini}}(t_i)\rangle \langle \mathbf{u}_k^{\text{ini}}(t_i)| \right] \mathbf{M}^\dagger(t_i, t) | \mathbf{F} \rangle, \\ &= \langle \mathbf{F} | \mathbf{M}(t, t_i) \mathbf{\Sigma}_{\text{ini}} \mathbf{M}^\dagger(t_i, t) | \mathbf{F} \rangle, \end{aligned} \quad (3.9a)$$

$$\begin{aligned} \sigma_{\text{sto}}^2(t) &= \frac{1}{N} \sum_{k=1}^N \int_{t_i}^t ds \int_{t_i}^t ds' \langle \mathbf{F} | \mathbf{M}(t, s) | \mathbf{f}_k^{\text{sto}}(s) \rangle \langle \mathbf{f}_k^{\text{sto}}(s') | \mathbf{M}^\dagger(s', t) | \mathbf{F} \rangle, \\ &= \int_{t_i}^t ds \int_{t_i}^t ds' \langle \mathbf{F} | \mathbf{M}(t, s) \left[\frac{1}{N} \sum_{k=1}^N |\mathbf{f}_k^{\text{sto}}(s)\rangle \langle \mathbf{f}_k^{\text{sto}}(s')| \right] \mathbf{M}^\dagger(s', t) | \mathbf{F} \rangle, \\ &= \int_{t_i}^t ds \langle \mathbf{F} | \mathbf{M}(t, s) \mathbf{\Sigma}_{\text{sto}} \mathbf{M}^\dagger(s, t) | \mathbf{F} \rangle, \end{aligned} \quad (3.9b)$$

where $\mathbf{\Sigma}_{\text{ini}}$ and $\mathbf{\Sigma}_{\text{sto}}$ are the variance matrices for initial and stochastic disturbances, respectively. Here we have used the properties of the white noise, both for oceanic initial condition and atmospheric stochastic disturbances: $\langle \mathbf{u}_k^{\text{ini}}(t_i) | \mathbf{u}_l^{\text{ini}}(t_i) \rangle = \sigma_{\text{ini}}^2 \delta_{k,l}$ and $\langle \mathbf{f}_k^{\text{sto}}(s) | \mathbf{f}_l^{\text{sto}}(s') \rangle = \sigma_{\text{sto}}^2 \delta_{k,l} \delta(s - s')$ where $\delta_{k,l}$ is the Kronecker delta and $\delta(s - s')$ is the Dirac delta function. The $\mathbf{\Sigma}_{\text{ini}}$ and $\mathbf{\Sigma}_{\text{sto}}$ matrices are diagonal where the terms on the diagonal are the variances of the uncertainty at each particular locations. It is important to note that these variance matrices do not provide a norm but a pseudo norm, since local variances can be zero, leading to singularities in the operators. These equations (3.9) demonstrate that the knowledge of the oceanic initial condition and atmospheric stochastic forcing variances, together with the propagation of the cost function by the adjoint is enough to diagnose at all times the evolution of the system variance measured through the cost function.

3.3.3 Application to an idealized stochastic model

To illustrate our ability to compute the ensemble spread without running an ensemble we apply our method to an idealized stochastic model of anomalous Sea Surface Temperature (SST), where both oceanic initial condition uncertainty (white noise with $\sigma_{\text{SST}}=5\times 10^{-2}$ K) and atmospheric stochastic forcing (white noise with $\sigma_{\text{SAT}}=0.3$ K) are imposed. The stochastic idealized model is derived from Hasselmann (1976) and Frankignoul and Hasselmann (1977), and reads:

$$d_t \text{SST}_k(t) = -\gamma [\text{SST}_k(t) - \text{SAT}_k(t)], \quad (3.10)$$

where SST_k and SAT_k are random realizations of anomalous Sea Surface Temperature and Surface Atmospheric Temperature, respectively; k is the index of the random realization or of the individual member of the ensemble, and γ is the inverse of an oceanic damping time scale set to 10 yr.

Using this model we compute the ensemble spread through (3.9). Indeed, the solution of this idealized model of a Langevin equation is an Ornstein-Uhlenbeck process which can be determined analytically (see for example section 3.4 in Dijkstra, 2013). Hence, we obtain the evolution of the oceanic uncertainties in the context of the idealized model as:

$$\sigma_{\text{ini}}^{\text{id}^2}(t) = \sigma_{\text{SST}}^2 e^{-2\gamma(t-t_i)}, \quad (3.11a)$$

$$\sigma_{\text{sto}}^{\text{id}^2}(t) = \frac{\gamma}{2} \sigma_{\text{SAT}}^2 [1 - e^{-2\gamma(t-t_i)}]. \quad (3.11b)$$

To validate the analytical result we also diagnose the total uncertainty from a large ensemble of 1,000 members (differing in their random realization of both oceanic initial condition uncertainty – $\text{SST}_k(0)$ – and atmospheric stochastic forcing – $\text{SAT}_k(t)$, Fig. 3.1a). As expected these two diagnostics are identical (Fig. 3.1b), although the former is far more quantitatively accurate and computationally efficient (a single simulation vs 1,000 ones). Also, (3.9) allows us to attribute at each lead time the relative contribution of the two uncertainties in the total variance (Fig. 3.1c), which cannot be disentangled robustly with a classical forward integration of a large ensemble.

3.4 Application to a detailed ocean GCM

3.4.1 Experimental set-up

To apply the exact same procedure as in section 3.3.3, but now in a more realistic setting, we use a forced ocean GCM (NEMO-OPA 8.2, Madec et al., 1998) in a global realistic configurations (Madec and Imbard, 1996, with a horizontal resolution of $2^\circ \times 2^\circ$ and 31 vertical levels with a level distance ranging from 10 to 500 m). We also use its tangent and adjoint components (OPATAM, Weaver et al., 2003). The combined model configuration follows Sévellec and Fedorov (2017) and Chapter 2 under flux boundary condition.

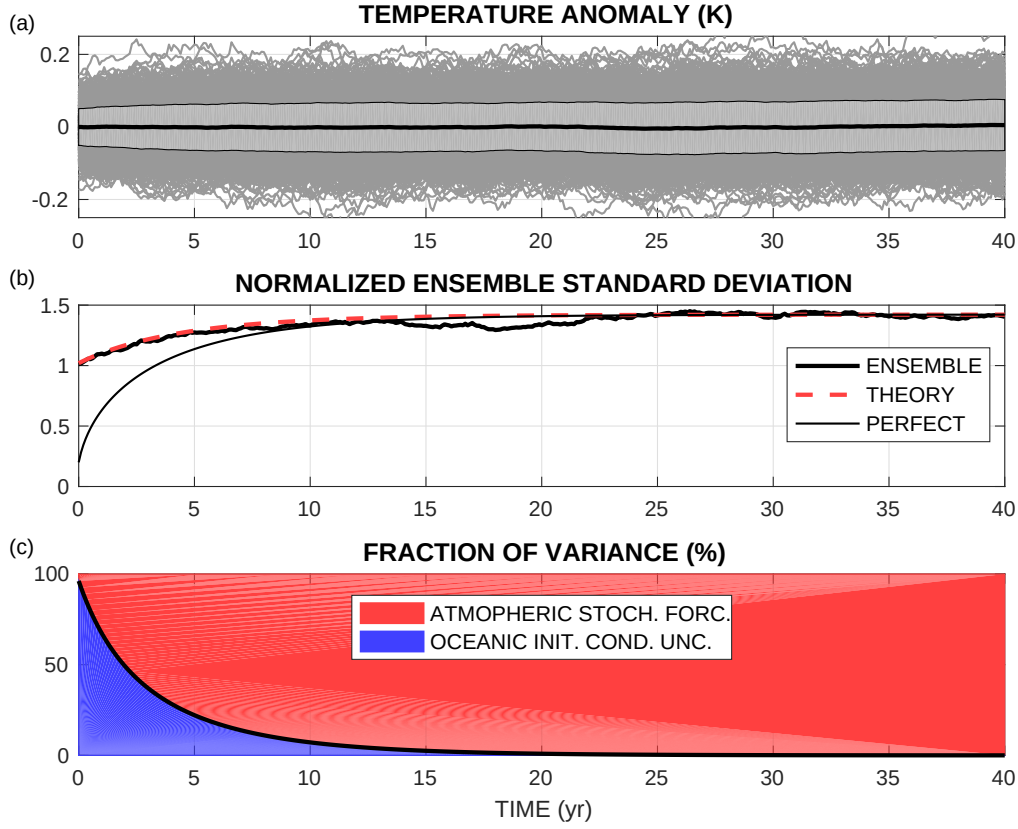


Figure 3.1: (a) Increase in anomalous Sea Surface Temperature uncertainty for the idealized stochastic model described in equation (3.10). Each grey lines correspond to individual members – $SST_k(t)$. Thick black line is the ensemble mean, and thin black lines together with the grey shaded region represent plus/minus one ensemble standard deviation. (b) The ensemble spread (thick black line) is equivalent to the theoretical result (red dashed line) following the sum of equations (3.11a) and (3.11b), whereas the perfect case (thin black line) represents the spread when initial condition uncertainty is ignored, uncertainty being restricted to the stochastic forcing following equation (3.11a). (c) Fraction of the variance between the two sources of uncertainty: (red) the atmospheric stochastic forcing following equation (3.11a) and (blue) the oceanic initial condition following equation (3.11b).

We refer the reader to this study for further details of the model configuration and the climatological background state used here.

Despite being the typical configuration used in current climate prediction systems and in the last Coupled Model Intercomparison Project (CMIP5, Taylor et al., 2012), the use of non-eddy-resolving model is not trivial. Indeed the ocean chaotic behaviour is absent from this low resolution model. However, the oceanic solutions of these type of models remain irregular through ocean-atmosphere interactions and the propagation of the atmospheric uncertainty in the (almost-laminar) ocean (Germe et al., 2017b). As a result, in this study we assume that the oceanic uncertainty is forced by the chaotic nature of the atmosphere. We select four typical ocean metrics of the North Atlantic. The intensity of the AMOC (MVT, measured as the meridional volume transport above 1,500 m at 50°N), the meridional heat transport (MHT, measured at 25°N), the spatially-mean SST (SST, average from 30°N to 70°N) and the oceanic heat content (OHC, measured as the mean temperature from 30°N to 70°N and from the surface to the bottom of the ocean).

The two sources of uncertainty are assumed to be represented by white noise. For the oceanic initial condition uncertainty, given our relative poor knowledge of its true nature (Germe et al., 2017a), we choose a spatially-uniform white noise. The intensity of this spatially-uniform white noise was determined from typical uncertainties in ocean observations. To this end we used error estimates from Argo float measurement in the North Atlantic (Debruyères et al., 2016). This dataset provides 10-day mean uncertainties after objective interpolation on a 2° by 2° and 20 dB uniform grid over the 2004-2015 period. From this dataset we have built a distribution (regardless of the time or of the horizontal and vertical locations of the uncertainties) for the mean ORCA2-grid volume after assuming the independence of the uncertainties. To estimate a typical uncertainty we computed the mode (most frequent value), the median and the mean of this error distribution. We obtained 0.001 K, 0.05 K and 0.13 K for these measures. (Note that typical error values for salinity are roughly equivalent after rescaling them in term of temperature, using a linear equation of state for seawater: 0.005 K, 0.04 K, and 0.12 K.) Hence, to cover the full range of uncertainties, we use three intensities: low with a standard deviation of 0.025 K, medium with 0.05 K and high with 0.1 K. These values allow us to test the role of this parameter and explore different plausible values. For the atmospheric stochastic forcing, we also assume a white noise representation. The uncertainty intensity follows the standard deviation of SST and SSS (Sea Surface Salinity) diagnosed from a long control simulation of the IPSL coupled model (Fig. 3.2), which used NEMO as its oceanic component (Mignot et al., 2013). To convert this temperature and salinity variations into tendency variations we scaled them with a typical atmospheric synoptic timescale of 7 days.

3.4.2 Error growth attribution

Using this experimental set-up together with (3.9), we are able to diagnose the exact theoretical growth of the uncertainty (Fig. 3.3a1-4) and can attribute the contribution of oceanic initial condition and atmospheric stochastic forcing to the total uncertainty (Fig. 3.3b1-4). To compare our results with previous studies we also diagnose the Predic-

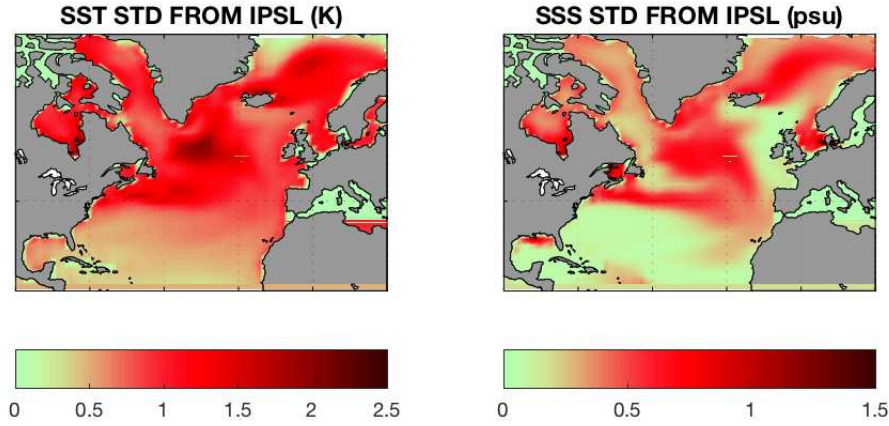


Figure 3.2: (a) and (b) Standard deviation of SST and SSS, respectively, from a long simulation of the IPSL model (Mignot et al., 2013). These standard deviations are used as the intensity of the atmospheric stochastic forcing. (Note that the atmospheric stochastic forcing is applied globally, despite being represented here only in the North Atlantic, region of interest of the study.)

tive Power such as $PP = 1 - \sigma^2(t)/\sigma_\infty^2$ (Schneider and Griffies, 1999), where σ_∞^2 is diagnosed as the variance of the ensemble spread in (3.5) evaluated at $t=40$ yr for a given metric (Fig. 3.3c1-4). This diagnostic is 0 if the uncertainty reaches its asymptotic value and 1 if negligible (negative values suggest that the uncertainty exceeded asymptotic value).

Our analysis shows that the uncertainty for the SST metric is almost equal to its asymptotic value after a few years (Fig. 3.3a3). Also, the oceanic initial condition uncertainty does not seem to play an important role for SST (Fig. 3.3b3). This suggests that the atmospheric synoptic noise is the main driver of the error growth. This leads to a rather weak Predictive Power over the 40 yr tested (Fig. 3.3c3), suggesting that our ability to predict (i.e., potential prediction skill of) SST is restricted to values of less than 20% of its long-term variance and to interannual time scales. We emphasize, however, that this metric is not well represented in a forced ocean context. Hence conclusions from this experimental set-up might not be directly applicable to the coupled climate system.

For the three other metrics (MVT, MHT, and OHC) the uncertainty reaches its asymptotic value on much slower, multidecadal time scales (Fig. 3.3a1, 2, and 4). For OHC, however, the standard deviation is still slightly increasing at 40 yr. This might be problematic since $\sigma^2(40 \text{ yr}) < \sigma_\infty^2$, which potentially leads to an underestimation of the Predictive Power. Unlike SST, the OHC metric is also sensitive to the oceanic initial condition uncertainty. In the perfect case (absence of oceanic initial condition uncertainty), the error growth increases almost monotonically with time (Fig. 3.3a4), leading to an almost linear decrease of the Predictive Power from 1 to 0 over the 40 yr tested (Fig. 3.3c4). This suggests that, in the absence of oceanic initial condition uncertainty, OHC has a predictive skill

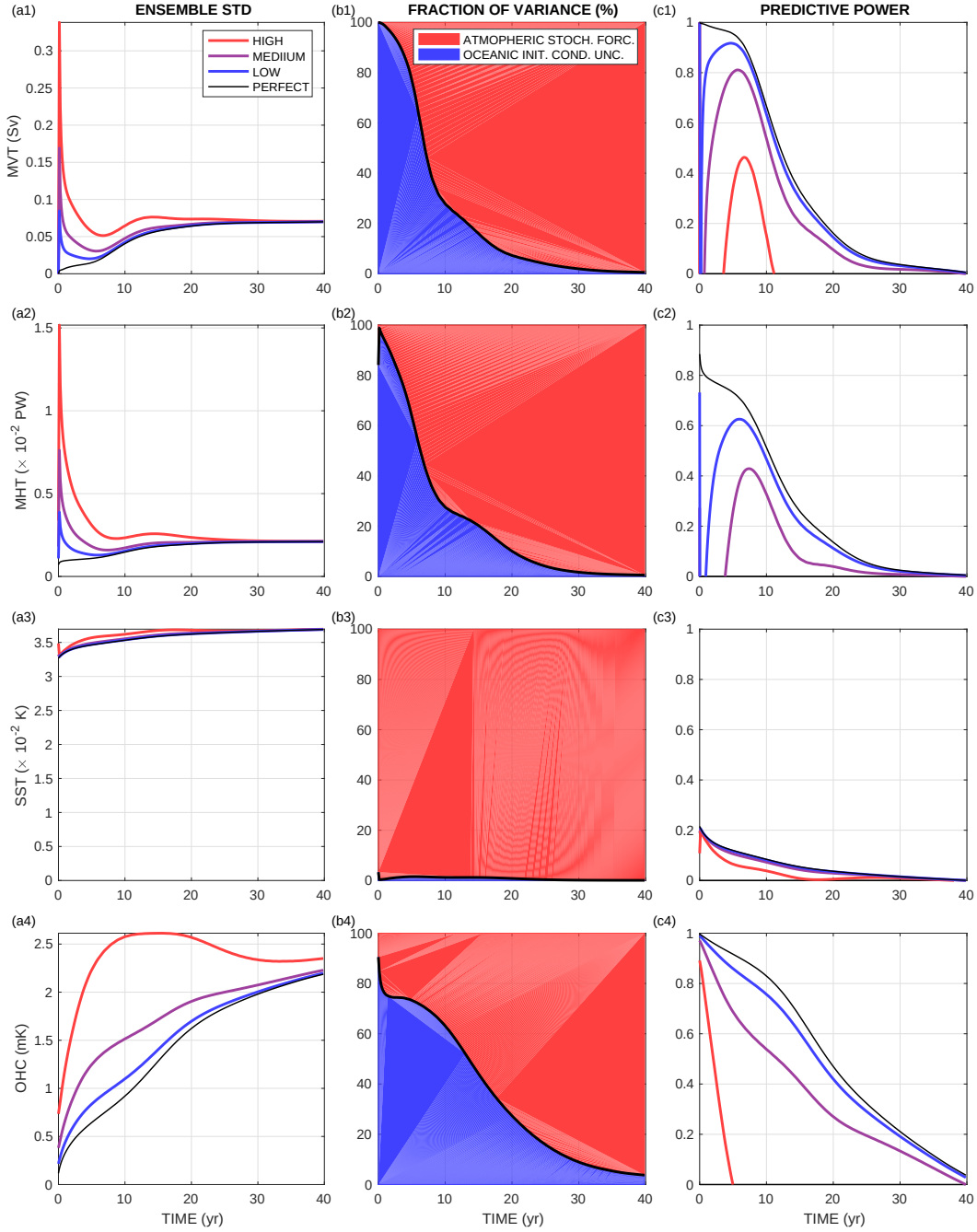


Figure 3.3: (a1-4) Growth in the uncertainty using NEMO for four metrics of the North Atlantic ocean: (a-c1) Meridional Volume Transport at 50°N and 1,500 m depth (MVT), (a-c2) Meridional Heat Transport at 25°N (MHT), (a-c3) Sea Surface Temperature averaged in the Atlantic from 30°N to 70°N (SST), (a-c4) temperature averaged in the Atlantic from 30°N to 70°N and from surface to bottom (OHC). The thick solid lines correspond to a uniform uncertainty in the oceanic initial condition of (blue – high) 0.025 K, (purple – medium) 0.05 K and (red – low) 0.1 K of standard deviation. The black thin line represents the perfect case where the oceanic initial condition uncertainty are neglected. (b1-4) Attribution of uncertainty growth between atmospheric stochastic forcing and oceanic initial condition, using the medium uncertainty for the latter (0.05 K). (c1-4) as (a1-4) but for Predictive Power [PP=1- $\sigma^2(t)/\sigma_\infty^2$, where σ_∞^2 is evaluated at 40 yr].

that remains above 80% up to a decade, above 50% up to 20 yr, and below 20% after 3 decades. When not neglected the impact of oceanic initial condition uncertainty are mainly occurring over the first two decades (Fig. 3.3a4). Depending on the intensity of this error it can significantly impact the Predictive Power (Fig. 3.3c4). In the most extreme case it suggests the absence of potential prediction skill after only 5 years. In this case it induces a slight overshoot (a variance bigger than the asymptotic value) of the OHC variance peaking between 10 and 20 yr. This implies that an initial error of such an intensity has huge repercussion on prediction systems by pushing them beyond their natural attractor. However, using the average value for the oceanic uncertainty, we find that it dominates the error growth on time scales up to 15 yr, with a maximum impact of 75% of the error growth on interannual time scales (Fig. 3.3b4). This suggests that accurate oceanic initial condition can improve significantly the potential prediction skill of OHC on interannual to decadal time scales.

The two last metrics (MVT and MHT) show the same overall behaviours, but differ from OHC. In the absence of oceanic initial condition uncertainty, the two error growths increase with time until a saturation value is reached around 20-30 years (Fig. 3.3a1-2). This reflects on the predictive powers as an almost monotonous decrease in the exception of a plateau over the first ~ 5 years (Fig. 3.3c1-2). When an oceanic initial condition uncertainty is applied the instantaneous error growth of the two metrics becomes huge, regardless of the applied intensity (Fig. 3.3a1-2). This suggests that initial error on the oceanic field can lead to an overshoot of MVT and MHT variability, even for relatively weak intensity (0.025 K). This is of importance for prediction systems since it suggests that such an error can push the system beyond its natural attractor. This result is consistent with the analysis of Sévellec and Fedorov (2017). They demonstrated that small spatial-scale disturbances of the density field have important impacts on both MVT and MHT, because MVT and MHT are controlled by local East-West density differences. (This result is summarized in the Appendix.) Consequently, oceanic initial condition uncertainty removes any predictability on short interannual time scales, regardless of its intensity (Fig. 3.3c1-2). However, these small spatial-scale disturbances disappear quickly because of the relatively fast effect of horizontal diffusion on them (Sévellec and Fedorov, 2017). This leads to a “sweet spot” for prediction around 5-10 yrs for meridional volume and heat transport. This originates from the sharp decrease of the oceanic uncertainty and the relatively slow increase of the atmospheric forcing uncertainty. Hence on interannual to decadal time scales the oceanic initial condition uncertainty dominates the error growth, whereas on decadal to multidecadal time scales the error growth is dominated by the atmospheric stochastic forcing for both MVT and MHT (Fig. 3.3b1-2). This suggests that MVT and MHT interannual to decadal predictions can be improved by a more accurate oceanic initialization.

It should be noted, however, that in a chaotic turbulent ocean, the sharp decrease in oceanic uncertainty might probably not take place. While the role of a small change in initial condition would still decrease on longer time-scales, stochastic internal noise from ocean turbulence should enhance oceanic uncertainty when time progresses. Nevertheless, this “sweet spot” for prediction that arises in laminar ocean models, suggests that in the

real ocean predictions 5-10 years ahead are still probably the most valuable in terms of signal to noise ratio.

3.5 An optimal monitoring system

3.5.1 Method

As mentioned earlier, to decrease the overall uncertainty, and so to increase potential predictability, we can reduce the oceanic initial condition uncertainty (unlike the stochastic atmospheric forcing uncertainty that will remain). This is particularly true for MVT, MHT and OHC, where oceanic initial condition uncertainty dominates the variance growth over interannual time scales. This reduction can be accomplished by a better monitoring system of the ocean state (i.e., accurate measurement of temperature and salinity). Here we show a way to design such an efficient monitoring system.

For this purpose we use the Linear Optimal Perturbation framework. The formulation of LOP is summarized in the appendix and we refer the reader to Sévellec et al. (2007) and Sévellec and Fedorov (2017) for further details. The LOP comprises the computation of the pattern of sensitivity to initial conditions for a given linear metric (such as MVT, MHT, SST and OHC). The LOP depends on the lag between the initial condition perturbation and the metric response (examples of LOPs for different lags and for the four cost functions are shown in Figs 3.7-4). As we will demonstrate, the LOPs are directly relevant for the design of monitoring system.

We first define the optimal perturbation for a given cost function (i.e., the pattern of temperature and salinity anomalies that leads to the biggest change in the given cost function). Following the Appendix, we obtain:

$$|\mathbf{u}^{\text{opt}}(t_i)\rangle = \pm \epsilon \frac{\mathbf{S}^{-1} \mathbf{M}^\dagger(t_i, t) |\mathbf{F}\rangle}{\sqrt{\langle \mathbf{F} | \mathbf{M}(t, t_i) \mathbf{S}^{-1} \mathbf{M}^\dagger(t_i, t) | \mathbf{F} \rangle}}, \quad (3.12)$$

where $\mathbf{S}$ and ϵ are a norm and a parameter setting a global normalization constraint on the LOP at time t_i , such as $\langle \mathbf{u}^{\text{opt}}(t_i) | \mathbf{S} | \mathbf{u}^{\text{opt}}(t_i) \rangle = \epsilon^2$. The system's response to the optimal perturbation gives the optimal variance and reads:

$$\sigma_{\text{opt}}^2(t) = \langle \mathbf{F} | \mathbf{u}^{\text{opt}}(t) \rangle^2 = \epsilon^2 \langle \mathbf{F} | \mathbf{M}(t, t_i) \mathbf{S}^{-1} \mathbf{M}^\dagger(t_i, t) | \mathbf{F} \rangle, \quad (3.13)$$

Combining (3.9a) and (3.12), one can rewrite the variance growth for any set of initial conditions as:

$$\sigma_{\text{ini}}^2(t) = \langle \mathbf{F} | \mathbf{u}^{\text{opt}}(t) \rangle^2 \frac{\langle \mathbf{u}^{\text{opt}}(t_i) | \mathbf{S} \mathbf{\Sigma}_{\text{ini}} \mathbf{S} | \mathbf{u}^{\text{opt}}(t_i) \rangle}{\epsilon^4}. \quad (3.14)$$

One can easily check this expression by substituting (3.12) into the numerator of the second term on the right hand side of (3.14) and using (3.13) and (3.9a). We define a re-normalization factor, δ , as:

$$\delta^4 = \langle \mathbf{u}^{\text{opt}}(t_i) | \mathbf{S} \mathbf{\Sigma}_{\text{ini}} \mathbf{S} | \mathbf{u}^{\text{opt}}(t_i) \rangle, \quad (3.15)$$

where δ has the same unit as $|\mathbf{u}\rangle$ and ϵ . Using (3.13), we can then express the error growth linked to oceanic initial conditions as:

$$\sigma_{\text{ini}}^2(t) = \sigma_{\text{opt}}^2(t) \left(\frac{\delta}{\epsilon} \right)^4. \quad (3.16)$$

This suggests that the variance of a set of initial conditions can be inferred from the optimal variance after applying a re-normalization factor (based on the local intensity of the initial condition uncertainty and the projection of it onto the optimal perturbation). This re-normalization factor is thus a way to go from a global initial uncertainty to the local one.

This last expression allows us to write the Predictive Power as:

$$\text{PP} = 1 - \left[\frac{\sigma_{\text{sto}}^2(t)}{\sigma_{\infty}^2} + \frac{\sigma_{\text{opt}}^2(t)}{\sigma_{\infty}^2} \left(\frac{\delta}{\epsilon} \right)^4 \right], \quad (3.17)$$

where $\sigma_{\infty}^2 = \sigma^2(\infty) = \sigma_{\text{sto}}^2(\infty)$, since $\lim_{t \rightarrow \infty} \sigma_{\text{ini}}^2(t) = 0$ (i.e., the system is asymptotically stable, Sévellec and Fedorov, 2013a). This leads to the property that

$$1 - \frac{\sigma_{\text{sto}}^2(t) + \sigma_{\text{opt}}^2(t)}{\sigma_{\infty}^2} \leq \text{PP} \leq 1 - \frac{\sigma_{\text{sto}}^2(t)}{\sigma_{\infty}^2}. \quad (3.18)$$

This gives a lower and upper theoretical bounds to the Predictive Power.

This result has important consequences for the design of efficient monitoring systems. Indeed, increasing measurements in regions of high values of the LOP will decrease the initial condition uncertainty in those regions, hence reducing the re-normalization factor, since the latter is the norm of the LOP to the initial condition uncertainty. This will naturally increase the Predictive Power to its ideal value: $\text{PP}_{\text{Perfect}} = 1 - \sigma_{\text{sto}}^2(t)/\sigma_{\infty}^2$, since $\lim_{\delta \rightarrow 0} \sigma_{\text{ini}}^2(t) = 0$. This result also demonstrates the usefulness of data-targeting: one should decrease the uncertainty in regions of high intensity of the LOP.

We have tested this approach in the ocean GCM and found that data-targeting is indeed particularly efficient at decreasing the error growth. To define the optimal monitoring system we have normalized the time integral from 0 to 40-yr delay of absolute temperature and salinity patterns obtained from the LOPs. This gives us a relative sensitivity to initial condition in terms of temperature and salinity at all time scales that can be mathematically expressed as:

$$\text{OOD} = \frac{1}{2} \left[\frac{\tilde{T}}{\max(\tilde{T})} + \frac{\tilde{S}}{\max(\tilde{S})} \right], \quad (3.19a)$$

$$\tilde{T} = \int_0^{40\text{yr}} dt_i |T(t_i)|, \text{ and } \tilde{S} = \int_0^{40\text{yr}} dt_i |S(t_i)|, \quad (3.19b)$$

where T and S are the optimal pattern of the LOP in terms of temperature and salinity from $|\mathbf{u}^{\text{opt}}(t_i)\rangle$ and OOD is the Optimal Observation Density (Fig. 3.4).

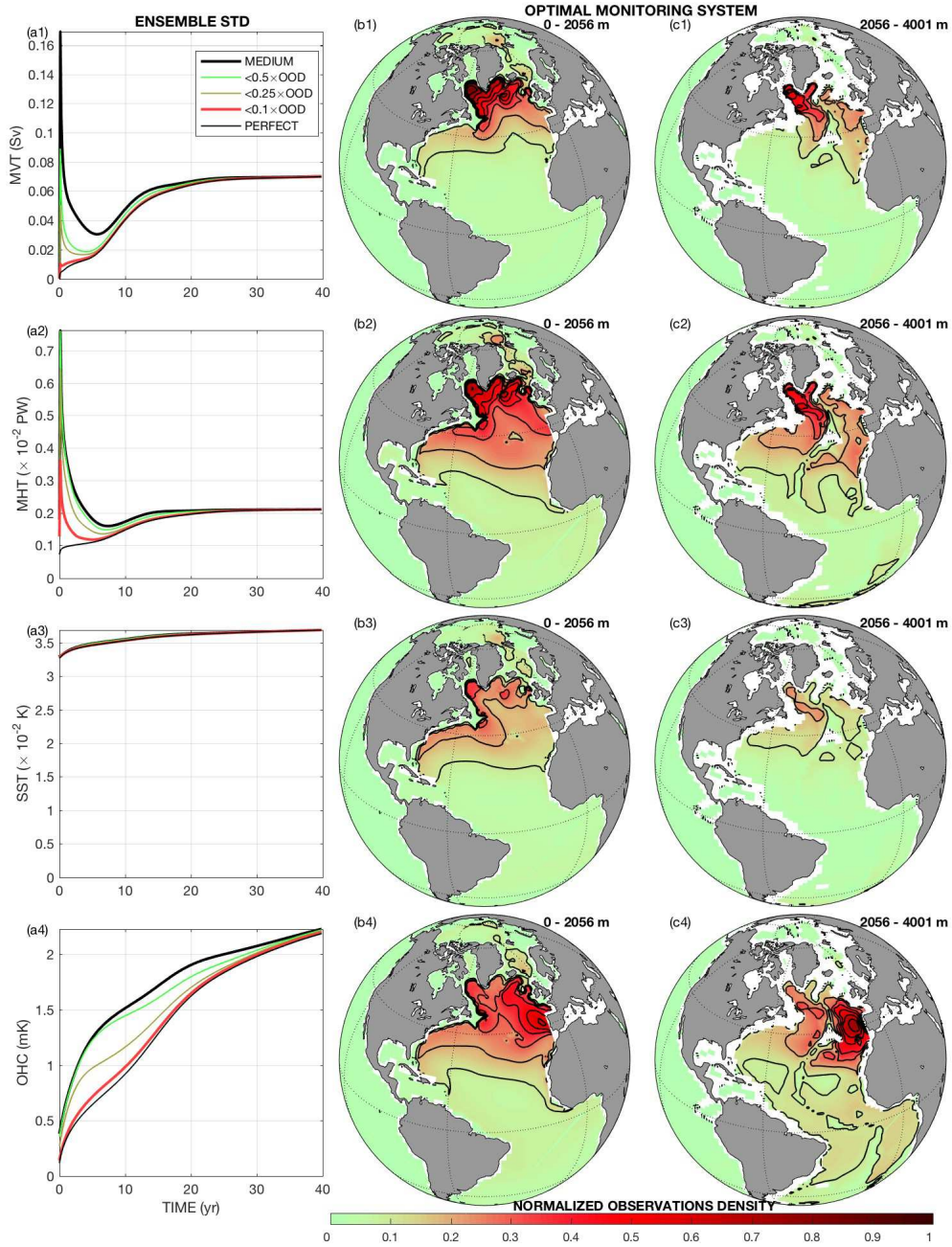


Figure 3.4: (a1-4) Error growth and (b1-4) optimal monitoring system following equation (3.19) in the upper (0-2056 m) and (c1-4) deep ocean (2056-4001 m) for (a-c1) MVT, (a-c2) MHT, (a-c3) SST and (a-c4) OHC metrics. Note that the definition of the deep ocean is below typical Argo floats coverage. (a1-4) The error growth decreases when uncertainty in the oceanic initial condition is decreased, from a uniform uncertainty of (thick black lines) 0.05 K of standard deviation, by removing uncertainty in region of high optimal observation density: no uncertainty for (green thin lines) $\text{OOD} > 0.5$, (brown thin lines) $\text{OOD} > 0.25$, and (red thick lines) $\text{OOD} > 0.1$. The decrease converges to the perfect case, where no uncertainty in the oceanic initial conditions is assumed (black thin lines).

Hence assuming no uncertainty in oceanic initial conditions in regions of high OOD (and modifying Σ_{ini} accordingly) we see a decrease in error growth, which converges to the perfect case (where oceanic initial condition uncertainty is neglected). This applies to all prediction time scales (Fig. 3.4a). Significant improvement is especially possible for the MVT with an optimal monitoring system that is quite narrow and mainly located in the Labrador Sea (Fig. 3.4b1, c1). SST does not show any improvement (Fig. 3.4a3). This is expected given the strong control of atmospheric stochastic forcing over error growth in SST (Fig. 3.3b3). MHT and OHC improvement remains possible (Fig. 3.4a2, a4) but the rather large scale spread of their OOD (Fig. 3.4b-c2, b-c4) suggests technical difficulty in monitoring accurately such large regions of the ocean.

3.5.2 Applicability to *in situ* measurements

The knowledge of OOD is extremely useful for fundamental understanding of the sensitivity regions of the ocean. However, it remains the question of the feasibility of its development, even as a guide to future monitoring systems. Hence it is fundamental to relate it to current *in situ* observational systems and in particular to their technological limitations.

In this context, it is interesting to note the high intensity of OOD below 2,000 m (Fig. 3.4c1-4, especially for OHC metric) which is currently the typical maximum depth of Argo float temperature and salinity measurements. This result, which has already been suggested in a wide range of studies (Wunsch, 2010; Dunstone and Smith, 2010; Heimbach et al., 2011; Germe et al., 2017b), implies that the maximum improvement in prediction skill can only be gained by also accurately monitoring the deep ocean, as soon possible with the development of Deep Argo floats.

Alternatively, monitoring arrays or specific scientific cruise transects can also act to reduce the uncertainty. To diagnose the best latitudinal location in the North Atlantic, we have computed the zonal and depth averages of the OOD for each metrics (Fig. 3.5). Our study suggests that, to be the most efficient to reduce prediction uncertainty, transects should be located around 55°N for MVT (northward to the MVT measurement at 50°N), whereas 35-45°N is the most efficient latitudinal band for MHT, SST and OHC. This suggests that the most efficient latitudes are always in the subpolar region rather than in the subtropical one (even for MHT despite being estimated at 25°N). In particular, our study suggests the usefulness of the OSNAP array (located between 53°N and 60°N, Lozier et al., 2016) compared to the RAPID array (located at 26.5°N, McCarthy et al., 2012) to reduce prediction uncertainties of the MVT metrics.

Beyond these more classical ocean monitoring systems, our method can also provide guidance for more innovative *in situ* ocean measurements, such as glider journeys. To this purpose we estimate the area covered by a single glider over a month. Following Wood (2010) and Gafurov and Klochov (2015) typical travel speed for Deepglider is 0.25 m s^{-1} and assuming a 160 km autocorrelation length scale for oceanic observations (Purkey and Johnson, 2010), we find: $\sim 100,000 \text{ km}^2$. On the other hand, from OOD we can compute the decrease of uncertainty per area monitored assuming that all depth are

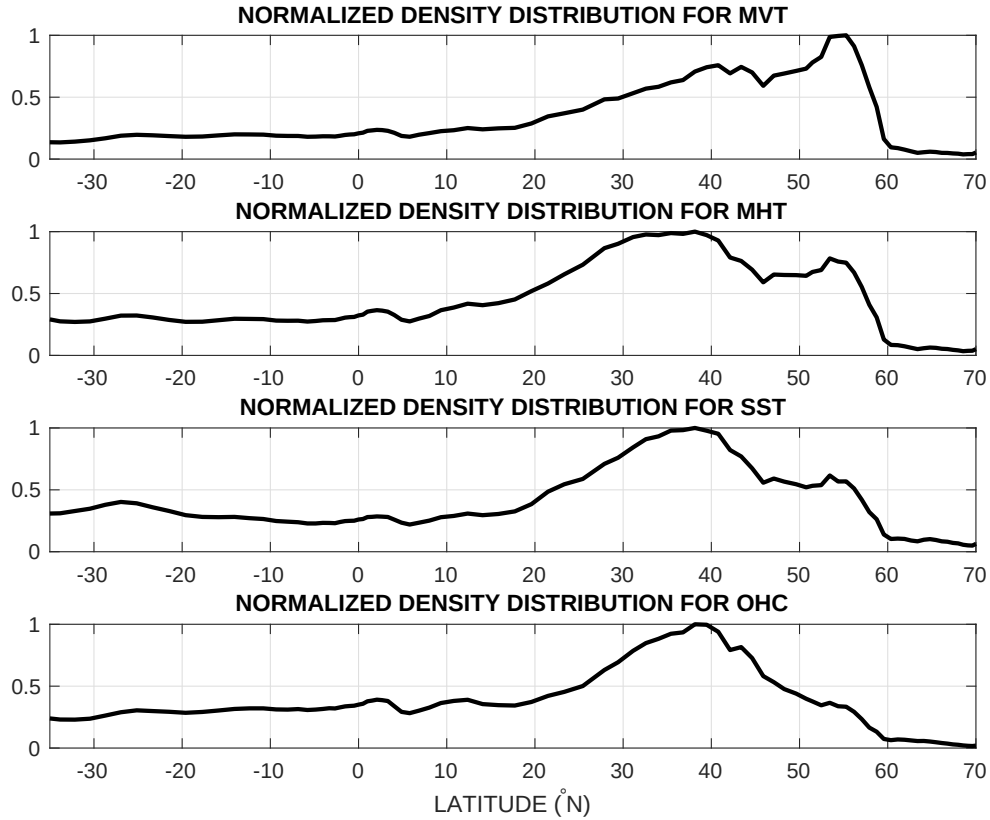


Figure 3.5: Normalized vertical and zonal average of the optimal monitoring system following (3.19) and shown in Fig. 3.4 for (a) MVT, (b) MHT, (c) SST, and (d) OHC. The maximum values show location where repeated transects or a mooring array would be the most efficient to reduce error growth in prediction.

monitored as now possible with Deepgliders (Fig. 3.6). Comparing these two estimates gives us the reduction for a glider fleet size (Fig. 3.6). Hence our estimation suggests that for a fleet of 70 gliders the uncertainty due to oceanic initial condition can be reduced by 90% for the first 5 years and by 80% for 10 years (Fig. 3.6). Even with only 15 gliders the error is already reduced by more than 70% on time scales from 1 to 5 years.

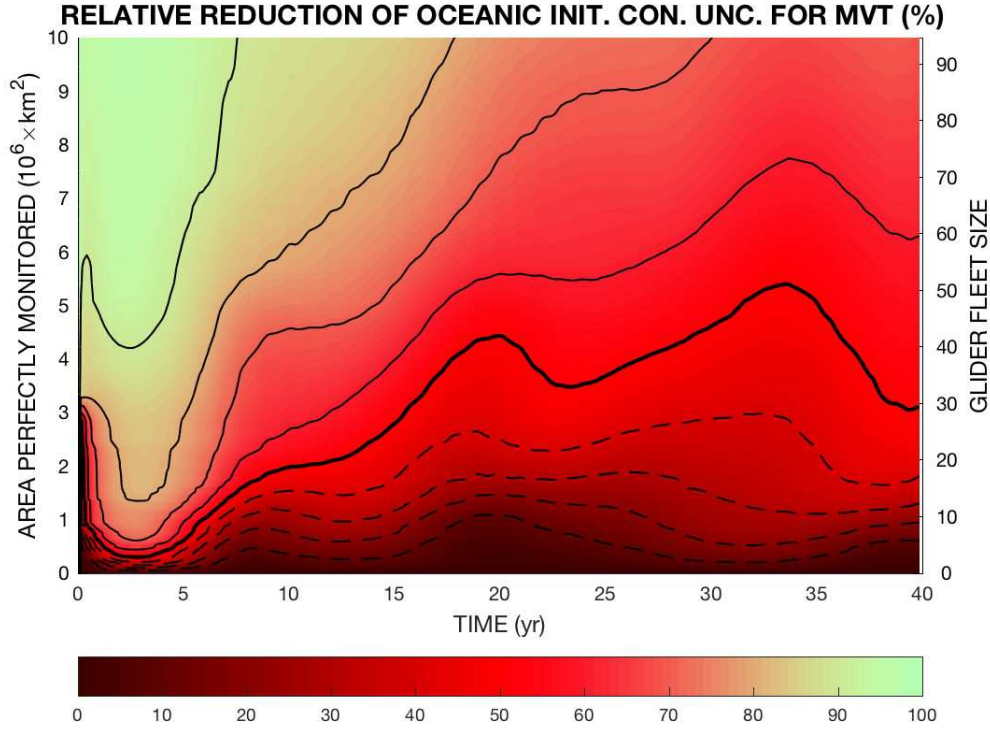


Figure 3.6: Relative reduction of the MVT error growth (due to oceanic initial condition uncertainty) as a function of monitored area following the optimal monitoring system (vertical average of Fig. 3.4b1 and c1). For comparison we have computed the gliders fleet number required to cover the monitored area in a month, assuming a 0.25 m per second travel speed (Wood, 2010; Gafurov and Klochkov, 2015) and a 160 km spatial correlation of observations (Purkey and Johnson, 2010). (Gliders are assumed to reach the bottom of the ocean, as now possible with Deepgliders.) Thick solid line is 50%, and thin dashed and solid lines are for lower and higher values, respectively; contour interval is 10%.

3.6 Discussion and Conclusion

In this study, we have focused on the North Atlantic to assess the predictability of four ocean metrics: the AMOC intensity (MVT at 50°N and above 1,500 m depth), the intensity of its heat transport (MHT at 25°N), the spatially-averaged SST over the North Atlantic (from 30°N to 70°N), and the spatial and depth averaged North Atlantic ocean temperature (from 30°N to 70°N). Here we propose a theoretical framework to quantitatively assess the growth of small perturbations.

Following the study of Chang et al. (2004), we have developed an exact expression of the ocean predictability for given metrics under 3 main assumptions. (i) The uncertainty remains small (linear assumption); (ii) the uncertainty follows a normal distribution (independence of uncertainties); and (iii) the ocean dynamics can be treated in a forced context (absence of explicit ocean-atmosphere feedback). In addition, this theoretical result allows us to separate the sources of uncertainty. We are thus able to attribute on a dynamical ground the relative role of internal oceanic initial condition uncertainty and of external atmospheric synoptic noise on ocean prediction uncertainty. After illustrating the method in an idealized model where analytic solutions are known (Hasselmann, 1976), the method has been applied to a state-of-the-art GCM (NEMO, Madec et al., 1998) in its 2° realistic configuration (ORCA2, Madec and Imbard, 1996). Given the importance of the model uncertainty on the time scales studied (Hawkins and Sutton, 2009b), it is worth noting that the single model approach used in this study limits the generalization of our results. Hence our developed framework needs to be applied to other ocean GCMs as well. In particular the location and intensity of deep convection, that is crucial for Meridional Volume Transport (Sévellec and Fedorov, 2015a), might be strongly model-dependent, potentially modulating the Optimal Monitoring System.

Our analysis suggests that spatially-averaged SST uncertainty is strongly dominated by the atmospheric synoptic noise (Fig 3.3b3), with a strong impact at all time scales, suggesting the limited predictability of this metric. The three other metrics (MVT, MHT and OHC, Fig 3.3b1, 2 and 4) are dominated ($\sim 80\%$) by oceanic initial condition uncertainty on interannual time scales (< 5 yr). Whereas the Predictive Power of OHC is monotonically decreasing suggesting the higher predictability of shorter time scales, MVT and MHT Predictive Power features a “sweet spot” at interannual time scales (Fig 3.3c). This means that MVT and MHT are especially predictable on 5-10 yr time scales where the signal to noise ratio peaks.

These results were obtained by focusing on the propagation of the error measured through the variance of its probability density function. We have shown that we can also compute solutions for other statistical moments, and so potentially reconstruct the entire probability density function. However, we are limited by two assumptions that restrict the generalization of our solutions. The first assumption is on the structure of the atmospheric stochastic forcing and of oceanic initial condition uncertainty. Assuming a Gaussian white noise leads to simplification in the mathematical treatment of the problem and allows an analytic solution. Hence, by construction our theoretical solution and its numerical application with the ocean GCM consider only random spatially-uncorrelated errors for the

oceanic initial condition uncertainties. However initial conditions uncertainties, which are often derived from ocean reanalysis for operational prediction systems, might not have such a useful property. They are often spatially correlated. This might change our results. In particular, this might eliminate the important interannual uncertainties for MHT and MVT due to rapid unbalanced errors. Hence, it would be ideal to generalize our theoretical result to a more general uncertainty. This will be a direction for future investigation. The other assumption is on the linearity of the dynamics which limits the behaviour that can be represented. For instance, the possible occurrence of qualitative changes in the probabilistic distribution (e.g., P-bifurcation), such as the change from an unimodal to a bi-modal distribution, cannot be captured. In this context other methods should be used such as the Pullback Attractor (e.g., Ghil et al., 2008) or Transfer Operator (e.g., Tantet et al., 2015) techniques. However they appear to be still computationally expensive and are currently only applicable for idealized models.

The dominance of oceanic initial condition uncertainty in the overall MVT, MHT and OHC uncertainty strongly suggests the possible improvement of predicting these metrics. This source of uncertainty can be reduced by an accurate monitoring of the oceanic state. By using LOPs to design an optimal monitoring system, reduction of such uncertainty is accomplished. Such monitoring systems can be done by the deployment of a suited mooring array or repeated transects at 35°N and 55°N. Alternatively, a fleet of gliders might be able to efficiently sample the important regions. We estimate that a fleet of 15 gliders can reduced the uncertainty due to oceanic initial condition by more than 70% on time scales from 1 to 5 years. Also, since gliders are a type of autonomous robotic vehicle, they can both monitor the suggested region and be re-oriented on the fly as the optimal monitoring system evolves. At an operational level our method coupled to a glider fleet would provide a self-adaptative network specifically designed for improving a prediction system.

The spatial resolution of the ocean model used here restricts the study of ocean dynamics to non-eddy regimes. Hence testing the role of oceanic mesoscale eddies is a direction for future work, that would require the extension of the current method to a fully nonlinear framework (following Conditional Nonlinear Optimal Perturbations by Mu and Zhang, 2006; Li et al., 2014, for instance). The ocean-only forced context of our analysis neglects the impact of large scale atmospheric feedbacks. However, Sévellec and Fedorov (2017) showed that the LOPs are only marginally modified by the ocean surface boundary conditions and Germe et al. (2017a) demonstrated that the overall expected behaviour of LOPs is conserved in a coupled context, despite a reduction of impact. We anticipate that both air-sea interaction and ocean turbulence impact the error growth. The “sweet spot” around 5-10 years for MVT and MHT, showing a minimum in uncertainty in the laminar ocean model, suggests that predicting these time scales in a fully coupled and eddy-resolving climate model is probably most valuable in terms of signal-to-noise ratio and that further development of the method outlined here to more complex Earth System Models is a promising route for improving climate predictions.

Appendix 3: LOP computation

Here, we summarize the calculation of the Linear Optimal Perturbation. The discussion closely follows a series of studies on similar topics (see Sévellec et al., 2007; Sévellec and Fedorov, 2017, for instance) and Chapter 2.

To find the optimal perturbation associated to a metric $\langle \mathbf{F} |$ under the constraint of the LOP falling within the initial condition uncertainty (i.e., a global size constraint or an average local variance constraint), we define the Lagrangian function as:

$$\mathcal{L}(|\mathbf{u}(t_i)\rangle, \gamma) = \langle \mathbf{F} | \mathbf{u}(t) \rangle - \gamma (\langle \mathbf{u}(t_i) | \mathbf{S} | \mathbf{u}(t_i) \rangle - \epsilon^2), \quad (3.20)$$

where t_i is the initial time (when the optimal initial perturbation is applied), t is the maximization time (when the cost function reaches its maximum value), and γ is a Lagrange multiplier. Furthermore, ϵ and $\mathbf{S}$ are a parameter and a norm, respectively, associated with the normalization constraint:

$$\langle \mathbf{u}(t_i) | \mathbf{S} | \mathbf{u}(t_i) \rangle = \iiint \frac{\alpha^2 T^2 + \beta^2 S^2}{V} dv = \epsilon^2, \quad (3.21)$$

where α and β are the thermal expansion and haline contraction coefficients, respectively; and dv and V are the unit and total ocean volumes. (Note that $\mathbf{S}$ is invertible since it represents a norm.) That is, ϵ measures the magnitude of the initial perturbation and restricts the perturbation to be within a globally average initial uncertainty and is set to $\epsilon/\alpha=1$ mK. The goal here is to maximize the cost function subject to this normalization constraint.

From expression (3.20) and the optimization condition $\delta\mathcal{L}=0$ the optimal initial perturbations are computed as

$$|\mathbf{u}^{\text{opt}}(t_i)\rangle = \pm \epsilon \frac{\mathbf{S}^{-1} \mathbf{M}^\dagger(t_i, t) | \mathbf{F} \rangle}{\sqrt{\langle \mathbf{F} | \mathbf{M}(t, t_i) \mathbf{S}^{-1} \mathbf{M}^\dagger(t_i, t) | \mathbf{F} \rangle}}. \quad (3.22)$$

Hence we can bound the impact of the initial disturbances as:

$$\langle \mathbf{F} | \mathbf{u}^{\text{opt}}(t) \rangle = \langle \mathbf{F} | \mathbf{M}(t, t_i) | \mathbf{u}^{\text{opt}}(t_i) \rangle = \pm \epsilon \sqrt{\langle \mathbf{F} | \mathbf{M}(t, t_i) \mathbf{S}^{-1} \mathbf{M}^\dagger(t_i, t) | \mathbf{F} \rangle}. \quad (3.23)$$

Examples of LOPs and their predicted impact are displayed in Figs 3.7, 3.8, 3.9, and 3.10, using MVT, MHT, SST, and OHC for their cost functions, respectively. They have been studied in detail by Sévellec and Fedorov (2017) and Chapter 2. Here, we summarize their relevant behaviours for this study. Depending on the cost function, LOPs are dramatically different. For OHC and SST, LOPs are basin-scale anomalies acting most efficiently on interannual to decadal time scales (Figs 3.10, 3.9); for MVT and MHT, LOPs have also a small spatial-scale signature and act most efficiently instantaneously (Figs 3.7, 3.8). This can be rationalized by the intrinsic characteristics of the metrics. Whereas, MVT and MHT are virtually equivalent to East-West density differences (that can be induced by both small and large spatial-scale disturbances), OHC and SST are basin-scale

spatial-averages of temperature field (filtering-out their sensitivity to small spatial-scale disturbances). All the LOPs have important signature in the deep ocean (included below 2,000 m).

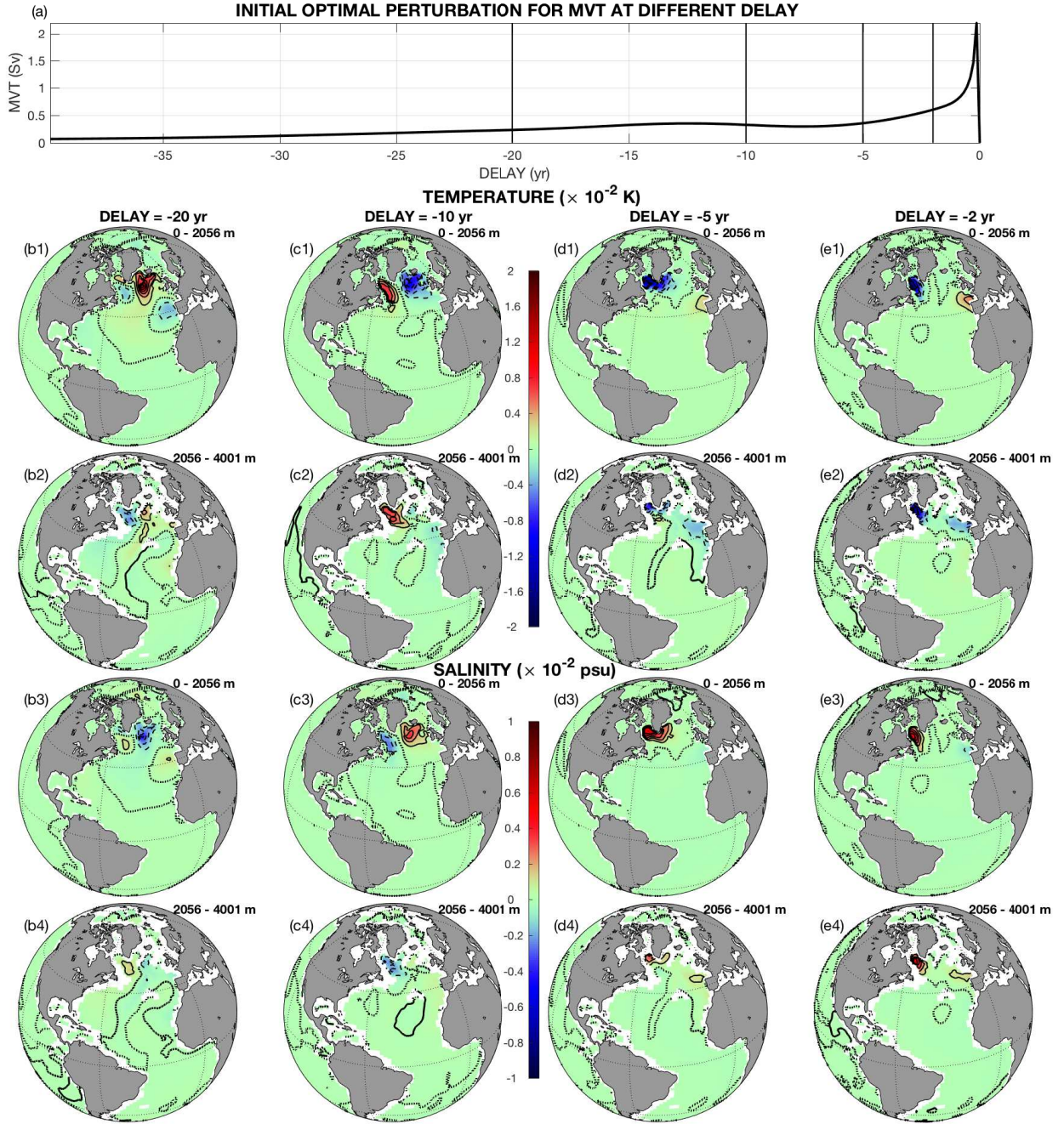


Figure 3.7: Linear optimal perturbations of the MVT metrics. (a) The MVT response to LOP is computed for delay ranging from 0 to 40 yr. (b-d) four examples of LOP for delay of 2, 5, 10 and 20 years, as indicated by the vertical lines in (a): (b1-4) 0-2056 m average temperature, (c1-4) 2056-4001 m average temperature, (d1-4) 0-2056 m average salinity, (e1-d4) 2056-4001 m average salinity. For comparison all LOPs are normalized by $\sqrt{\langle \mathbf{u}^{\text{opt}}(t_i) | \mathbf{S} | \mathbf{u}^{\text{opt}}(t_i) \rangle} / \alpha = 1 \text{ mK}$.

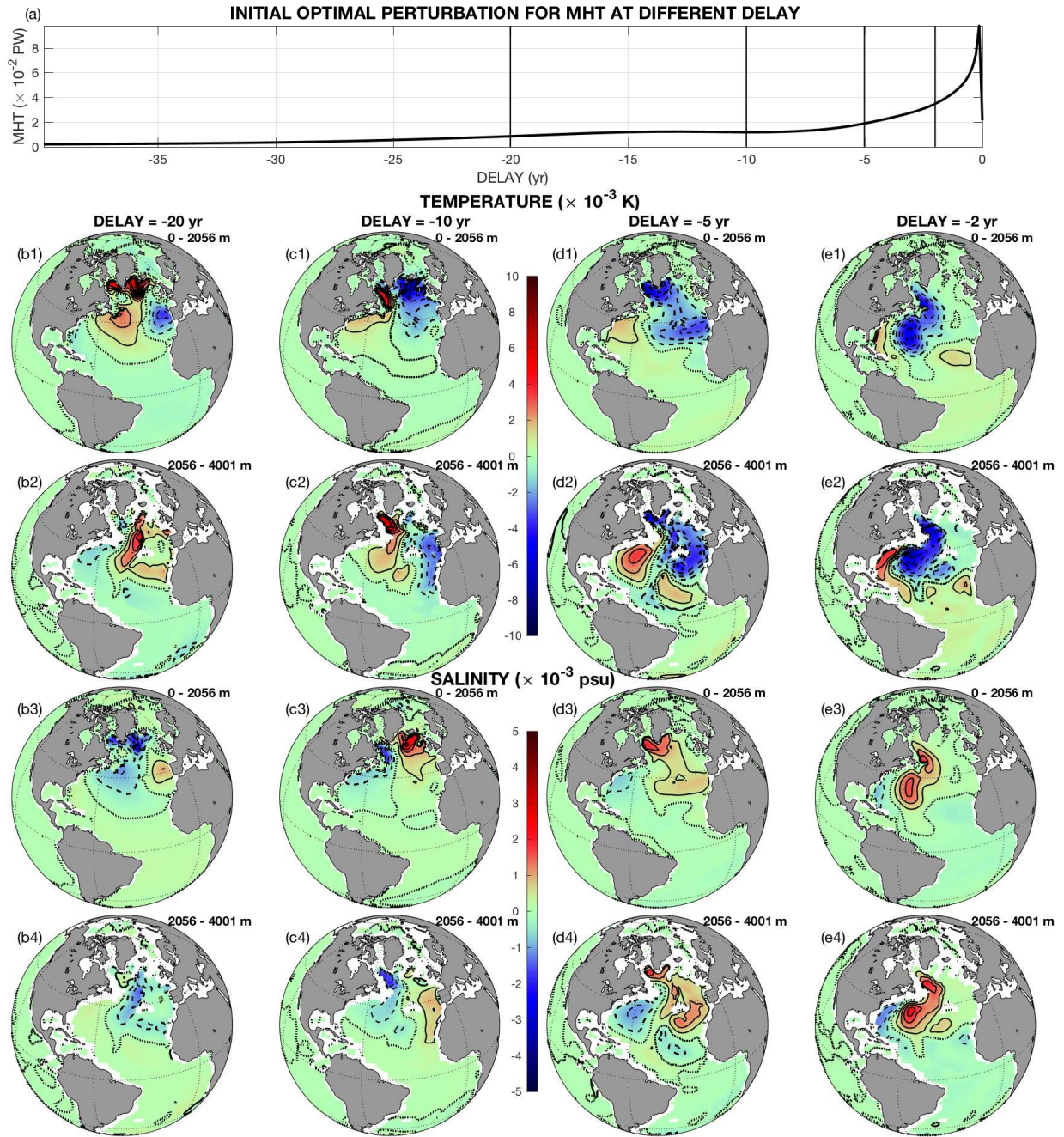


Figure 3.8: As Fig. 3.7 but for the MHT metric.

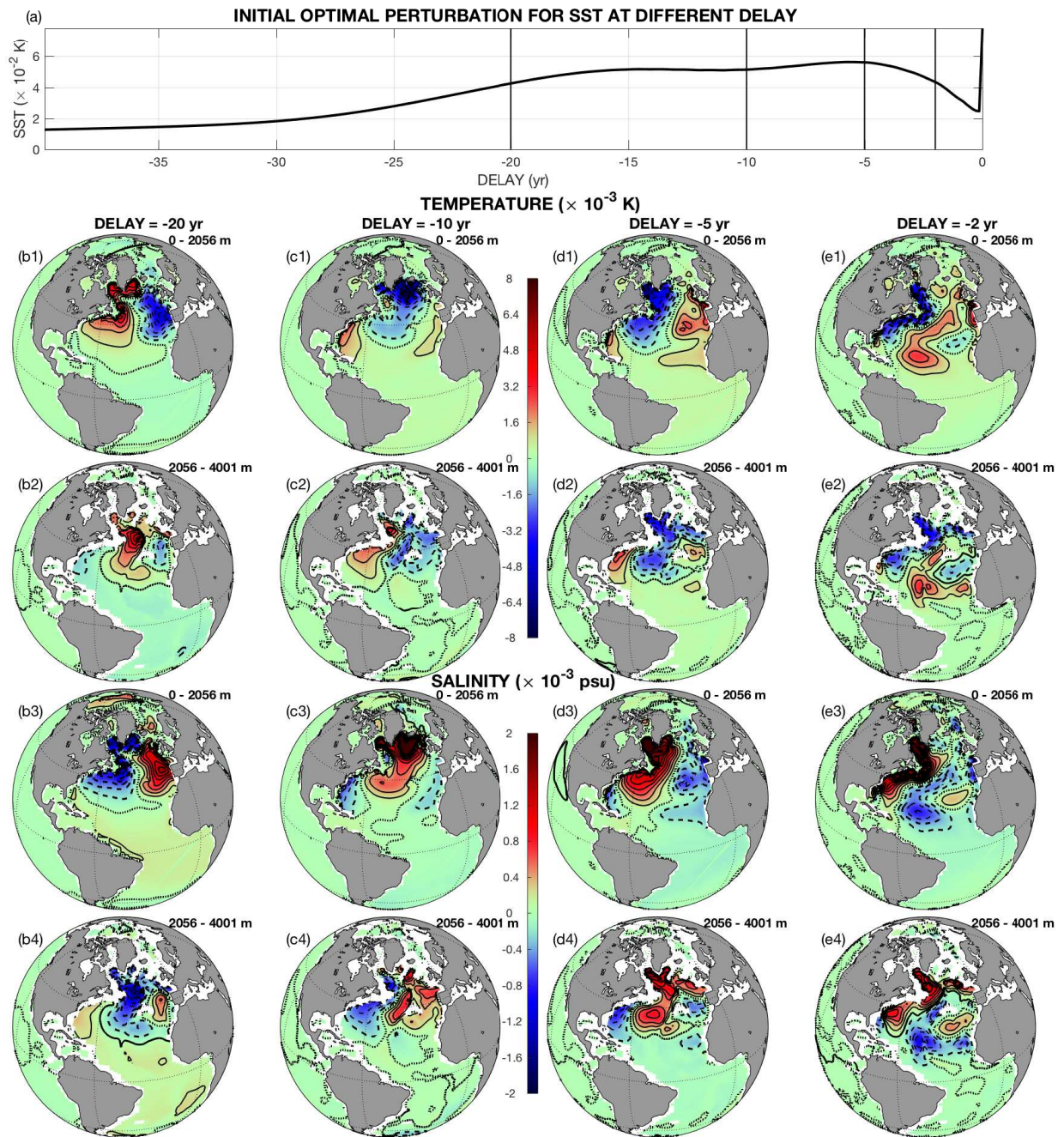


Figure 3.9: As Fig. 3.7 but for the SST metric.

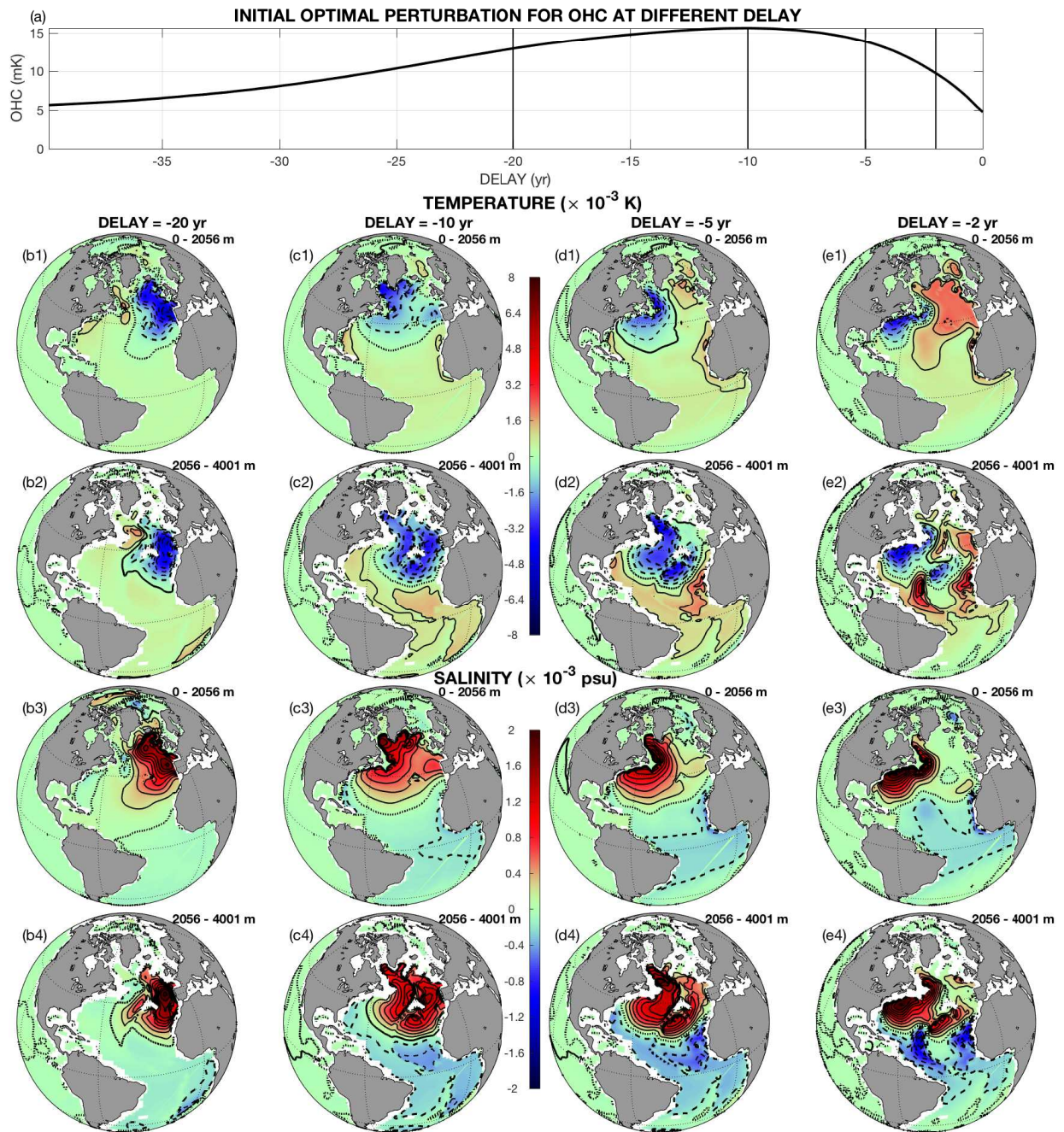


Figure 3.10: As Fig. 3.7 but for the OHC metric.

Chapter 4

Beyond the Current Knowledge

This work was done in collaboration with S. Mueller and A. Germe.

4.1 A way forward

One of the overarching limitations of the previously described work (Chapters 2 and 3) is the inherent linear assumption. To overcome it, we have developed a fully-nonlinear method that we describe below.

4.1.1 Methodology

The method is based on a fully non-linear minimization method: OCTOPUS (Optimal Computation of Targeted Outcomes for Prediction Using an iterative Solver), that we have developed for the purpose of predictability studies. This iterative method follows four steps:

1. Pre-computation: Computation of the model-target distance;
2. Linear framework: Computation of the LOP allowing the optimal reduction of the distance;
3. Weakly nonlinear framework: Computation of the optimal intensity of the LOP;
4. Fully nonlinear framework: adding the perturbation, computed in (2), scaled by the intensity, computed in (3), to the fully non-linear model and update the model-trajectory as well as the model-target distance used in (1).

These steps are repeated until required convergence is achieved (Fig. 4.1). Step 1 to 3 are fully described in Sévellec and Fedorov (2013b) and the procedure has been applied in Mueller and Sévellec (2017a, in preparation), which most of the results below follow. As a proof of concept we apply this method to a synthetic perturbation in NEMO-ORCA2 (Fig. 4.2). This perturbation corresponds to a temperature anomaly, that reads:

$$T_{\text{syn}} = e^{\frac{z}{h}} Re \left[Y_9^{-5} (\text{lon}, \text{lat}) \right], \quad (4.1)$$

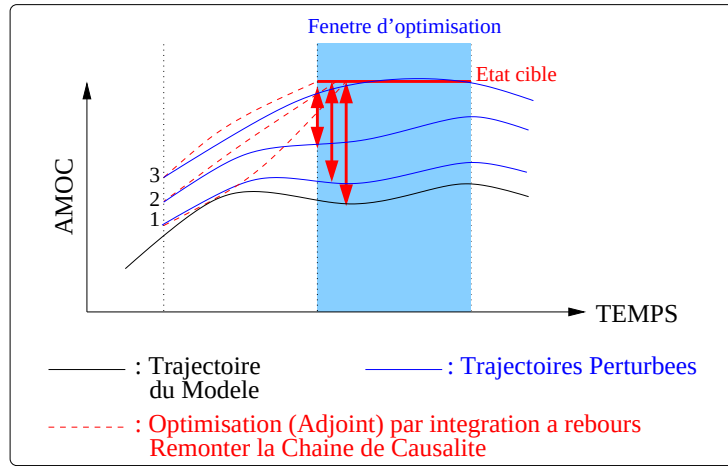


Figure 4.1: Schematic of the OCTOPUS methodology. The NOP (Nonlinear Optimal Perturbation) can be found iteratively by adding the LOP (Linear Optimal Perturbation, Sévellec and Fedorov, 2013b) that minimized the distance between the trajectory and the target over the optimization window.

where h is the vertical scale of the anomaly set to 500 m and $Y_9^{-5}(\text{lon}, \text{lat})$ is the spherical harmonic function setting the horizontal shape of the anomaly, chosen to be large but still sub-basin scale in both longitude and latitude.

The goal here is to reconstruct the synthetic perturbation applied at time -180 days by minimizing the distance (measured using the thermohaline norm presented in previous chapters) between the unperturbed trajectory and the perturbed one over the optimization window set between -90 and 0 days (Fig. 4.2b).

Our procedure allows us to rebuild the synthetic anomaly (Fig. 4.3). Already, after a single iteration, more than 30% of the bias (distance between the perturbed and the unperturbed trajectories) is removed; after 10 iterations more than 60% of the bias is removed; and after 250 iterations the bias is reduced to 5% of its initial value. With this number of iterations, the synthetic perturbation is reconstructed by more than 75% (Fig. 4.4).

It is interesting to note that the long term behavior is also well reconstructed by the method (Fig. 4.4a). Consistently with the analysis of Chapter 2, this suggests that the large scale pattern of the synthetic perturbation has been accurately reconstructed (Fig. 4.4b) and the reconstruction error is mainly restricted to smaller spatial scales, which have a weaker impact on the long term behavior of the system.

The convergence of our solution demonstrates the usefulness of our method (Fig. 4.4). Also its skillful application in ORCA025 configuration (not shown) demonstrates the ability of the non-linear method to be useful and accurate in an eddy-permitting model.

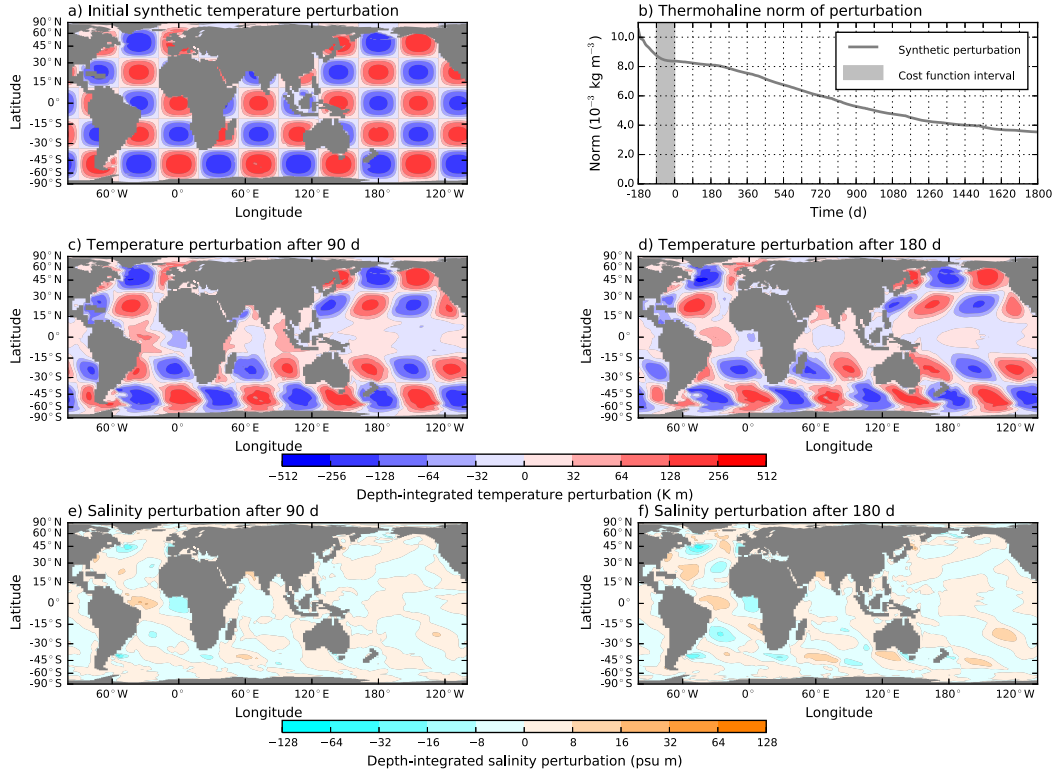


Figure 4.2: (a) Shape of the synthetic temperature perturbation. (b) Evolution of the perturbed trajectory measured through the thermohaline norm (point by point distance in terms of density). The shaded grey region indicates the optimization window used to reconstruct the synthetic temperature perturbation. (c,d) Temperature perturbation after 90 and 180 days (i.e., at time -90 and 0 days), respectively; and (e,f) salinity perturbation after 90 and 180 days (i.e., at time -90 and 0 days), respectively. All fields are vertically integrated.

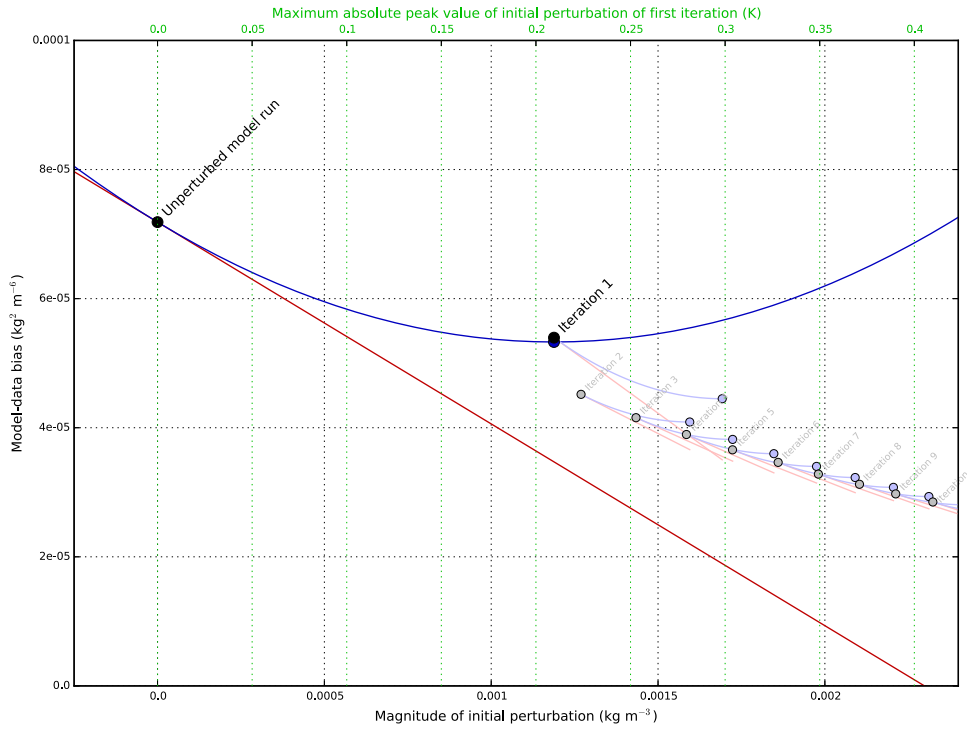


Figure 4.3: Iterations of the OCTOPUS method to reach the NOP and to reconstruct the synthetic perturbation. Red lines and blue parabolae show the results within the linear and weakly nonlinear frameworks, respectively. The dots denote the actual results from the fully nonlinear update.

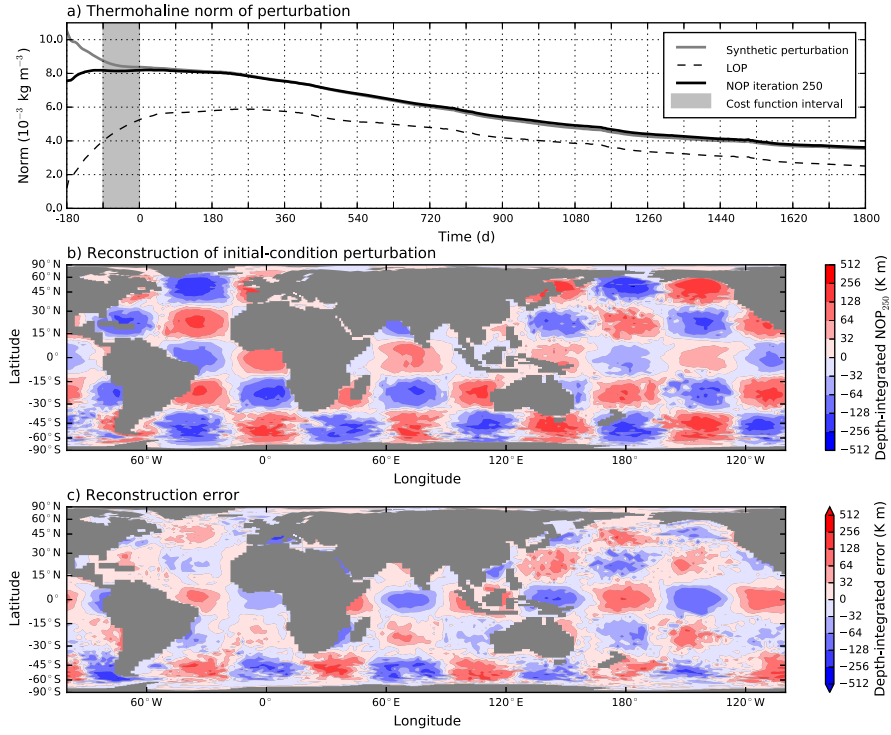


Figure 4.4: (a) Evolution of the thermohaline norm perturbed at time -180 days by the synthetic perturbation (thick grey line), by the LOP (thin dashed line), and by the NOP at iteration 250 (thick black line). The shaded grey region indicates the optimization window used to reconstruct the synthetic temperature perturbation set from -90 to 0 days. (b) Reconstructed perturbation, NOP, at iteration 250 in terms of temperature. (c) Temperature difference between the reconstructed and synthetic perturbations at iteration 250. All fields are vertically integrated.

4.1.2 Preliminary results

Beyond this methodological proof-of-concept, we can build on OCTOPUS to develop a new methodology aiming to estimate the likelihood of a range of climate states rather than focusing on predicting the exact future climate state. In this framework, we are not predicting the exact oceanic condition of 2018, for example, but the likelihood for 2018 of a dramatic slow-down event of the AMOC, a particularly typically strong AMOC, a mild value of the AMOC, and so on. This is done in two steps: (1) targeting different climate states defined by the intensity of their meridional ocean circulation, strength of meridional oceanic heat convergence, or upper ocean heat content, for instance; (2) estimating their likelihood. The first step is done using OCTOPUS and the second one, which is still currently in development, is done through examination of the shape and intensity of the perturbations obtained with OCTOPUS.

As an example, we have applied this method to study interannual variations of the AMOC. Here, the AMOC is measured at 26.5°N , latitude of the RAPID monitoring system that has recorded the AMOC since 2004 (McCarthy et al., 2012). From there, 12 targeted states of annual AMOC one year ahead are set. These range from 0 to 22 Sv by a 2-Sv increment (Fig. 4.5). Then OCTOPUS methodology is used to find the “closest” initial conditions or smallest perturbations that reach each of these 12 scenarios.

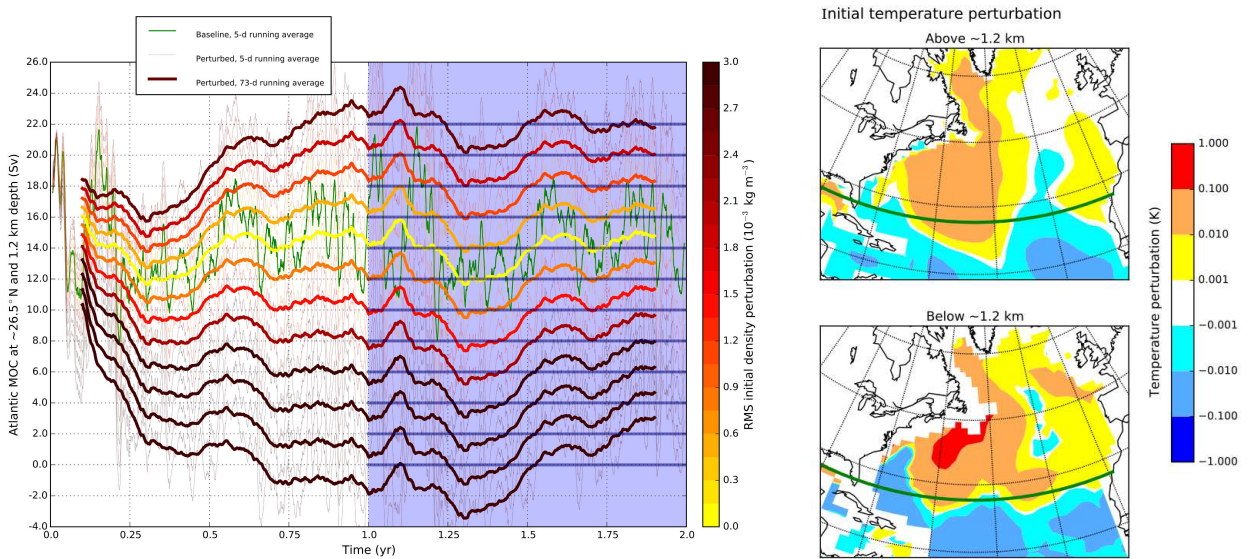


Figure 4.5: (left) Example of the OCTOPUS method used to generate an ensemble targeting a range of 12 AMOC states from 0 to 22 Sv (horizontal blue lines) between year 1 and 2 (blue region). The color of the curves represents the intensity of the perturbation (NOPs) applied to the initial condition (Mueller and Sévellec, 2017b, in preparation). (Right) The most efficient perturbation (NOP), in terms of temperature, inducing an AMOC of 0 Sv between year 1 and 2 (top and bottom panels show averaged values above and below $\sim 1,200$ m, respectively).

This example suggests that the precursor of a transient shutdown of the AMOC (the

smallest non-linear perturbation leading to a 0-Sv AMOC over a year) is characterized by a warming in the east subpolar region (Fig. 4.5 right). This warming is intensified below 1,000 m and mainly located north of the North Atlantic Current along the west Atlantic boundary. This suggests that to predict the risk of AMOC dramatic changes one-year ahead, one should monitor the temperature of the Deep Western Boundary Current. More generally, all the precursors (i.e., for the 12 selected targets) show roughly the same pattern. This highlights that monitoring the Deep Western Boundary Current is also useful to predict more moderate slow-downs of the AMOC and even increases (that would be associated to a cooling). However this almost-linear relation between precursors and AMOC responses, despite the use of a non-linear method, might be related to the relatively low resolution of the model used in this study ($2^\circ \times 2^\circ$). Hence, such results would need to be confirmed in eddy-permitting or even eddy-resolving models.

4.2 Conclusion & Directions for future work

Here we have demonstrated the usefulness of our iterative method to compute and study dramatic and moderate changes in the AMOC. However, for direct application of this method to prediction and predictability studies one major question still need to be addressed. Indeed, despite knowing the exact shape of the perturbation able to disrupt the AMOC, for instance, the link between this nonlinear perturbation and the likelihood of such a disruption remains unclear. The computation of the likelihood depends on the size and shape of the obtained perturbation (i.e., the NOP) that “pushes” the current climate toward the future targeted one (i.e., “How hard is it to get there?”) and on the detectability of the perturbation (i.e., ‘Can current observing systems monitor such perturbations?’). In simplified terms, is the perturbation small or big? And, for the latter, is it located in well-monitored regions? Hence, if the perturbation is small or if it is big but undetectable, the targeted state is considered to be likely (light colours in Fig. 4.5). On the other hand, if the perturbation is big and in a well-monitored region, the targeted state is considered to be unlikely (dark colours in Fig. 4.5). These considerations will be directions for future work.

Beyond the purely oceanographic application, the computation of perturbations for a range of targeted states, and their transcription into likelihood, will allow the computation of risk assessment of climate changes. In particular, by applying this method in state-of-the-art coupled climate models, we will be able to generate dramatic climate scenarios or events, and test their risk. Preliminary works have demonstrated our ability to significantly modify the ocean heat content in a coupled context (Fig. 4.6 left, Germe et al., 2017a). In this study we have evaluated the risk of European heat waves (Fig. 4.6 right), cold European winters, and persistent droughts around Mediterranean basin induced by a change in oceanic heat content. Thus, applying such a method in state-of-the-art climate models is an important direction for improving interannual-to-decadal climate prediction systems.

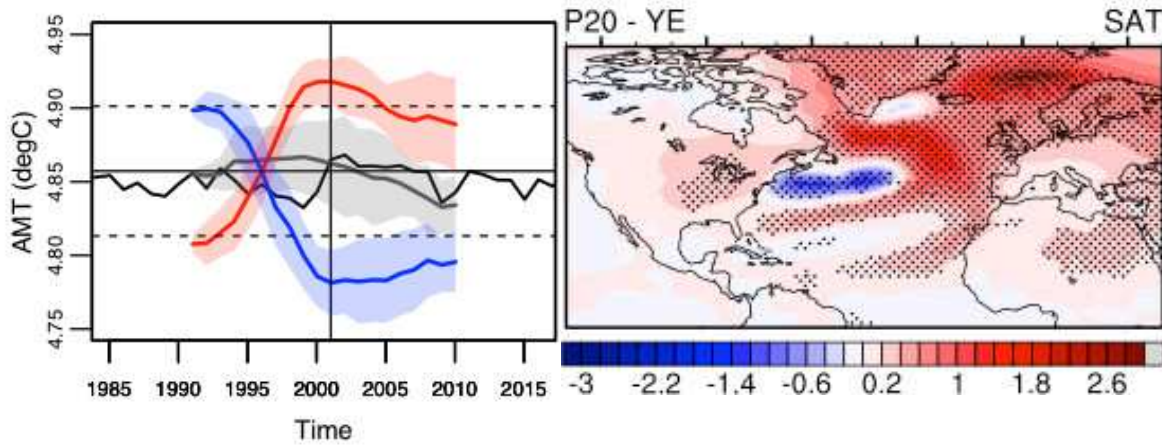


Figure 4.6: (left) Ensemble simulations of the state-of-the-art coupled IPSL model (Marti et al., 2010) perturbed to induce the maximum change in North Atlantic ocean heat content (Germe et al., 2017a). As expected, the positive anomaly (dark red) increases the ocean heat content after ~ 12 yr, whereas the negative anomaly (dark blue) reduces it. In the absence of an anomaly (control ensemble in grey and control run denoted by the thick black line) the heat constant remains constant. The three experiments have been reproduced for an ensemble of 10 different atmospheric initial conditions (generated as a white noise) to acknowledge the atmospheric uncertainty. The ensemble is denoted by the shaded regions (99% confidence level) around the corresponding bold line representing the ensemble mean. (Right) Consequences of the ocean heat content warming after 5-10 years in term of annual average of surface atmospheric temperature. The dots show regions which are significantly different from the control ensemble (95% confidence level). A strong warming occurs in the East Atlantic and from northern Europe to Russia.

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Scientific Contributions

SC.1 List of Publications

Invited contributions are denoted by an asterisk (*),

Contributions from supervised students or sponsored postdocs – by an obelisk (†).

Publications

2017:

- 28. **Sévellec, F.**, H. A. Dijkstra, S. S. Drijfhout, and A. Germe, 2017: Dynamical attribution of oceanic prediction uncertainty in the North Atlantic - Application to the design of optimal monitoring systems, accepted in *Climate Dynamics*.
- 27. **Sévellec, F.**, A. V. Fedorov, and W. Liu, 2017: Arctic sea ice decline weakens the Atlantic Meridional Overturning Circulation, *Nature Climate Change*, 7, 604-610.
- 26. **Sévellec, F.**, A. Colin de Verdière, and M. Ollitrault, 2017: Evolution of intermediate water masses based on Argo float displacements, *J. Phys. Oceanogr.*, 47, 1569-1586.
- 25. **Sévellec, F.** and A. V. Fedorov, 2017: Predictability and decadal variability of the North Atlantic ocean state evaluated from a realistic ocean model, *J. Climate*, 30, 477-498.
- † 24. Germe, A., **F. Sévellec**, J. Mignot, D. Swingedouw and S. Nguyen, 2016: On the Robustness of near term climate predictability regarding initial state uncertainties, *Climate Dynamics*, 8, 353-366.

2016:

- 23. **Sévellec, F.**, B. Sinha and N. Skliris, 2016: The rogue nature of hiatuses in a global warming climate, *Geophys. Res. Lett.*, 43, 8169-8177.
- 22. **Sévellec, F.** and A. V. Fedorov, 2016: AMOC sensitivity to surface buoyancy fluxes: Stronger ocean meridional heat transport with a weaker AMOC?, *Climate Dynamics*, DOI 10.1007/s00382-015-2915-4.

21. **Sévellec, F.** and T. Huck, 2016: Geostrophic closure of the zonally-averaged Atlantic Meridional Overturning Circulation, *J. Phys. Oceanogr.*, 46, 895-917.

2015:

20. **Sévellec, F.** and A. V. Fedorov, 2015: Unstable AMOC during Glacial Intervals and Millennial Variability: the Role of Mean Sea Ice Extent, *Earth and Planetary Science Letters*, 429, 60-68.
19. Ortega, P., J. Mignot, D. Swingedouw, **F. Sévellec** and E. Guilyardi, 2015: Reconciling two alternative mechanisms behind bi-decadal AMOC variability, *Prog. Oceanogr.*, 137, 237-249.
18. **Sévellec, F.**, A. C. Naveira Garraabato, J. A. Brearley, and K. L. Sheen 2015: Vertical flow in the Southern Ocean estimated from individual moorings, *J. Phys. Oceanogr.*, 45, 2209-2220.
17. **Sévellec, F.** and T. Huck, 2015: Theoretical investigation of the Atlantic multi-decadal oscillation, *J. Phys. Oceanogr.*, 45, 2189-2208.
- * 16. **Sévellec, F.** and A. V. Fedorov, 2015: Optimal excitation of AMOC decadal variability: links to the subpolar ocean, *Prog. Oceanogr.*, 132, 287-304.
15. Huck, T., O. Arzel and **F. Sévellec**, 2015: Multidecadal variability of the overturning circulation in presence of eddy turbulence, *J. Phys. Oceanogr.*, 45, 157-173.

2014:

14. **Sévellec, F.** and A. V. Fedorov, 2014: Millennial variability in an idealized ocean model: predicting the AMOC regime shifts, *J. Climate.*, 27, 3551-3564.
13. Manucharyan, G., W. Moon, **F. Sévellec**, A. Wells, J-Q. Zhong and J. Wettlaufer, 2014: Steady turbulent density currents on a slope in a rotating fluid, *J. Fluid Mech.*, 746, 405-4036.

2013:

12. **Sévellec, F.**, J. J.-M. Hirschi and A. T. Blaker, 2013: On the near-inertial resonance of the Atlantic meridional overturning circulation, *J. Phys. Oceanogr.*, 43, 2661-267.
11. **Sévellec, F.** and A. V. Fedorov, 2013: Model bias reduction and the limits of oceanic decadal predictability: importance of the deep ocean, *J. Climate*, 26, 3688-3707.
10. **Sévellec, F.** and A. V. Fedorov, 2013: The leading, interdecadal eigenmode of the Atlantic meridional overturning circulation in a realistic ocean model, *J. Climate*, 26, 2160-2183.

2011:

- * 9. **Sévellec, F.** and A. V. Fedorov, 2011: Stability of the Atlantic meridional overturning circulation in a zonally-averaged ocean model: the effects of freshwater flux, wind stress, and diapycnal diffusion, *Deep-Sea Research II*, 58, 1927-1943.

2010:

- * 8. **Sévellec, F.** and A. V. Fedorov, 2010: Excitation of SST anomalies in the eastern equatorial Pacific by oceanic optimal perturbations, *J. Mar. Res.*, 68, 597-624.
- 7. **Sévellec, F.**, T. Huck and A. Colin de Verdière, 2010: From centennial to millennial oscillation of the thermohaline circulation, *J. Mar. Res.*, 68, 597-624.

2009:

- 6. **Sévellec, F.**, T. Huck, M. Ben Jelloul and J. Vialard, 2009: Non-normal multi-decadal response of the thermohaline circulation induced by optimal surface salinity perturbations, *J. Phys. Oceanogr.*, 39, 852-872.

2008:

- 5. **Sévellec, F.**, T. Huck, M. Ben Jelloul, N. Grima, J. Vialard and A. T. Weaver, 2008: Optimal surface salinity perturbations of the meridional overturning and heat transport in a global ocean general circulation model, *J. Phys. Oceanogr.*, 38, 2739-2754.

2007:

- 4. **Sévellec, F.**, 2007: Variabilité basse fréquence endogène et exogène de la circulation thermohaline, Ph.D. thesis, Université de Bretagne Occidentale, Brest, France, 196pp.
- 3. **Sévellec, F.**, M. Ben Jelloul and T. Huck, 2007: Optimal salinity perturbations influencing the thermohaline circulation, *J. Phys. Oceanogr.*, 37, 2789-2808.

2006:

- 2. Colin de Verdière, A., M. Ben Jelloul, **F. Sévellec**, 2006: On the bifurcation structure of thermohaline oscillation, *J. Climate*, 19, 5777-5795.
- 1. **Sévellec, F.**, T. Huck, M. Ben Jelloul, 2006: On the mechanism of centennial thermohaline oscillations, *J. Mar. Res.*, 64, 355-392.

Publication in Revision

- * **Sévelle, F.** and B. Sinha, 2017: Predictability of Decadal Atlantic Meridional Overturning Circulation Variations, in revision for *Oxford Research Encyclopedia of Climate Science*.
- † Germe, A., **F. Sévelle**, J. Mignot, A. V. Fedorov, S. Nguyen and D. Swingedouw, 2017: The impacts of oceanic deep temperature perturbations in the North Atlantic on decadal climate variability and predictability, in revision for *Climate Dynamics*.

SC.2 Encadrement

PhD Students:

Victor Estella Perez – main advisor, since 2013;

- “Decadal Variability of the AMOC – role of the nonlinearities”,
- 2 co-signed publications in preparation.

Delphine Lobelle – main advisor, since 2015;

- “Potential collapse of the Atlantic Meridional Overturning Circulation”.

Dafydd Stephenson – main advisor, since 2016;

- “Toward a New Interannual to Decadal Prediction System”.

Guantong Lv – main advisor, since 2016;

- “Decadal Predictability of the AMOC – role of the ocean-atmosphere coupling”.

Rafael Jaume Catany – co-advisor, since 2013;

- “Impact of Ocean Conditions on the Development of Hurricanes”.

Postdocs:

Simon Müller – since 2014;

- Main sponsor,
- Funded by MESO-CLIP, SYCLOPE, and SMURPHS,
- 2 co-signed publications in preparation

Agathe Germe – 2013-2015;

- Co-sponsor,
- Funded through ENSEMBLE,
- 1 co-signed publication and 1 co-signed publication in revision,
- now Postdoc at NOCS, UK.

Panel Chair of PhD Students:

Helen Burns, since 2013;

- “Impacts of far field forcing on the Southern Ocean residual overturning circulation”.

Panel Chair for PhD Defense:

Freja K. Hunt, on 31 August 2017;

- “Global Warming and changing atmospheric teleconnection patterns”.

Master Projects:

Nikolaos Karapas – 2016-17,

- “Theoretical investigation of the inter-basin meridional overturning circulation”.

Mark Westaway – 2016-17,

- “The Warming Hole of the North Atlantic and the AMOC”.

Florent Aguesse – 2016-17,

- “Stability of Surface Boundary Current in the Subpolar North Atlantic”.

Cleo Jongedijk – 2016,

- “Predicting ENSO with transfer operator”.

Dafydd Stephenson – 2015-16,

- “Tracking passive tracers with an adjoint model – Application to the 18° Water”.

Undergraduate Projects:

Cyril Côme – 2016-17,

- “Wave Energy around UK”

Anna Jenkins – 2015,

- “Estimating turbulence from individual mooring”

Florent Aguesse – 2014,

- “Does a zonally-averaged closure for the large scale ocean circulation exist?”

Ben Smith – 2013-14,

- “Impact of wind on the bistability of the AMOC”

Asha Vijayeta – 2013,

- “Dynamics of the Bay of Bengal”

SC.3 Enseignement

Seminar Instructor:

- In **Advanced Methods in Physical Oceanography** (SOES6027), for postgraduate program in oceanography, 2015-17 (collaboration between University of Southampton, UK and Université de Bretagne Occidentale, France).
- In **Climate Dynamics** (SOES6006), for postgraduate program in oceanography, 2015-17 (University of Southampton, UK).
- In **Global Ocean Monitoring** (SOES6027), for postgraduate program in oceanography, 2013 & 2014 (University of Southampton, UK).
- In **Computational Data Analysis: part 3 – Signal Processing** (SOES3042 & SOES6025), for undergraduate and postgraduate program in oceanography, 2012 & 2013 (University of Southampton, UK).
- In **Ocean & Atmosphere dynamics: Essential Papers** (G&G 742a), co-taught with M.-L. Timmermans, for postgraduate program in geology and geophysics, 2010 (Yale University, CT, USA).

Guest Lecturer:

- In **Large Scale Ocean Processes** (SOES3010 & SOES6005), for undergraduate and postgraduate program in oceanography, 2012 & 2013 (University of Southampton, UK).
 - Lectures 10 & 11 on The Role of Mixing in Ocean Circulation.
- In **Climate Dynamics** (SOES6006), for postgraduate program in oceanography, 2012, 2013 & 2014 (University of Southampton, UK).
 - Lectures 8 & 9 on the Meridional Overturning Circulation Stability. (2012, 2013 & 2014)
 - Lecture 12 on Climate modeling (2012 & 2014).
 - Lecture 13 on Climate variability (2012 & 2014).
- In **Physical Oceanography** (G&G 535/335), for postgraduate program in geology and geophysics, 2011 (Yale University, CT, USA). Lecture on the ThermoHaline Circulation.
- In **Climate Modeling** (F&ES 771a), for master program in environmental management, 2011 (Yale University, CT, USA). Lecture on Ocean Circulation.
- In **Physical Oceanography** (G&G 535/335), for postgraduate program in geology and geophysics, 2010 (Yale University, CT, USA). Lectures 21 & 22 on Ocean Waves.

- In **Theory of Climate** (G&G 523/323), for postgraduate program in geology and geophysics, 2009 (Yale University, CT, USA).
 - Lecture 15 on Ocean General Circulation,
 - Lecture 18 on the Meridional Overturning Circulation and ThermoHaline Circulation.

Teaching Assistant:

- In **Nonlinear Dynamics and Chaos** for undergraduate program, third year of bachelor, 2005 (UBO, Brest, France).
- In **Atmospheric Dynamics** for postgraduate program in physical oceanography, 2004 (UBO, Brest, France).

Administrative Role:

- **MRes Ocean Science Program Leader**, coordination and recruitment of the Master Research in Ocean Science (University of Southampton), since 2016.
- **IT representative** for the department of Ocean and Earth Science at the University of Southampton, since 2013.

SC.4 Projets Scientifiques

- 2016-2020** Co-Investigator of NE/N005767/1, SMURPHS
▷ £450,855 over 4 years from Natural Environment Research Council (UK).
- 2017-2019** Co-Investigator of DECLIC
▷ 30,600€ over 3 yr from LEFE (CNRS, France).
- 2016-2018** Co-Investigator of Meso-Var-Clim
▷ 7,500€ over 3 yr from LEFE (CNRS, France).
- 2015-2016** Principal-Investigator of SYCLOPE
▷ £19,991 over 8 months from Southampton Marine and Maritime Institute (UK).
- 2013-2015** Principal-Investigator of NE/K005154/1, MESO-CLIP
▷ £198,219 over 2 yr from Natural Environment Research Council (UK).
- 2011-2014** Researcher Co-Investigator of DE-SC0007037
▷ \$401,000 over 3 yr from Department of Energy (USA).
- 2010-2013** Researcher Co-Investigator of Ti Ammo
▷ 27,000€ over 3 yr from LEFE (CNRS, France).

SC.5 Curriculum Vitæ

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Appointments

Mar. 2016-	ASSOCIATE PROFESSOR IN OCEAN PHYSICS. University of Southampton, Ocean and Earth Science, Southampton, UK
2012-2016	LECTURER IN OCEAN PHYSICS. University of Southampton, Ocean and Earth Science, Southampton, UK
2012 - 2013	LABORATORY ASSOCIATE IN OCEAN AND CLIMATE DYNAMICS. Yale University, Dpt of Geology and Geophysics, New Haven, CT, USA
2008 - 2011	POST-DOCTORAL POSITION IN OCEAN AND CLIMATE DYNAMICS. Yale University, Dpt of Geology and Geophysics, New Haven, CT, USA
2007 - 2008	POST-DOCTORAL POSITION IN PHYSICAL OCEANOGRAPHY. Laboratoire d'Océanographie et du Climat : Expérimentations et approches numériques, IPSL, Université Pierre et Marie Curie, Paris, France.

Professional Preparation

2003-2007	PHD IN PHYSICAL OCEANOGRAPHY. Université de Bretagne Occidentale, Brest, France.
2002-2003	1-YEAR POSTGRADUATE DIPLOMA IN PHYSICAL OCEANOGRAPHY. Université de Bretagne Occidentale, Brest, France.
2001-2002	1-YEAR MASTER'S DEGREE IN PHYSICS. Université de Bretagne Occidentale, Brest, France.
1998-2001	3-YEAR BACHELOR OF SCIENCE DEGREE IN PHYSICS. Université de Bretagne Occidentale, Brest, France.

Scientific Contributions

Publications	27 peer-reviewed including 22 as 1 st author.
Awards	300,000€ comme PI et 1,000,000€ comme Co-I depuis 2010.

Selected Synergistic Activities

Invited

Positions

- ▷ *Oct-Dec 2015: Researcher at KNMI, De Bilt, Holland.*
- ▷ *Aug-Sep 2015: Lecturer at Univ. Brest, Brest, France.*
- ▷ *Since Feb 2013: Consultant at Yale University, Dpt of G&G, New Haven, CT, USA.*

CTD watch

OVIDE June 2004

- ▷ *Oceanographic cruise from Greenland to Portugal, as part of the french project PNEDC and the international project CLIVAR.*

Conferences

(peer review)

Convener

- ▷ *Co-convener for OS1.3 session at EGU General Assembly 2014.*
- ▷ *Co-convener for NP2.2 session at EGU General Assembly 2012-15.*
- ▷ *Co-convener for AS39 session at AOGS General Assembly 2012.*
- ▷ *Co-convener for AS05 session at AOGS General Assembly 2011.*

Solicited talk

- ▷ *EGU 2012 – Sévellec, F. and A. V. Fedorov: Optimal surface temperature and salinity perturbations of the Atlantic meridional overturning circulation in a realistic ocean model.*
- ▷ *EGU 2012 – Sévellec, F. and A. V. Fedorov: Excitation of SST anomalies in the eastern equatorial Pacific by oceanic optimal perturbations.*
- ▷ *EGU 2011 – Sévellec, F. and A. V. Fedorov: Quantifying the limits of oceanic decadal predictability.*
- ▷ *EGU 2010 – Sévellec, F.: Predictability of the THC collapse in a chaotic idealized model.*
- ▷ *EGU 2009 – Sévellec, F.: Optimal perturbation and stability of the ocean circulation.*

Reviewer

Journal of Physical Oceanography (since Sep. 2007), *Climate Dynamics* (since Apr. 2009), *Journal of Climate* (since Jan. 2010), *Ocean Science* (since May 2011), *Dynamics of Atmospheres and Oceans* (since Oct. 2011), *Journal of Marine Research* (since Jul. 2012), *Geophysical Research Letters* (since Jan. 2013), *Paleoceanography* (since Jul. 2014)., and *Geophysical & Astrophysical Fluid Dynamics* (since Sep. 2016).

SC.6 Selected Publications

Beyond variability and predictability of the North Atlantic my research interest spans over a wide range of research topics from basin-scale to sub-mesoscale and from inertial timescale to 10,000-yr glacial-interglacial cycle (Fig. 4.7).

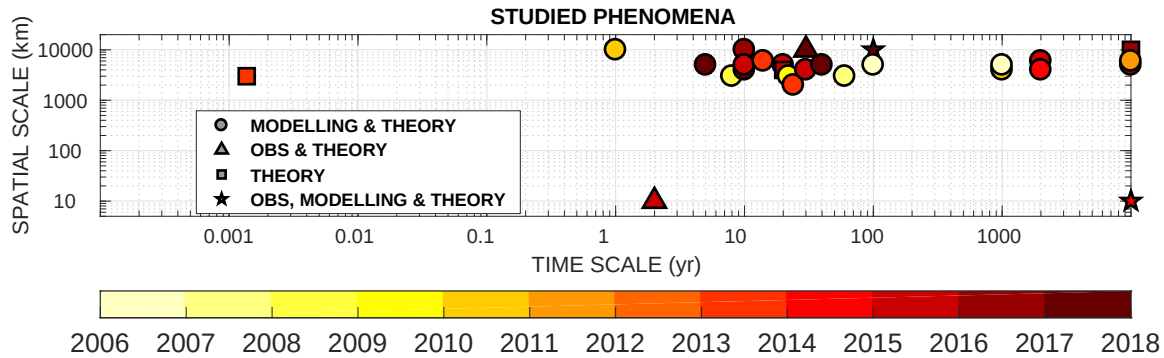


Figure 4.7: Synthesis of my previous work in term of spatial and temporal scales of studied phenomena. Markers reflect the type of approach and colors are the years of publication.

Here, I have selected 5 publications representative of this wide research interest. In particular, these 5 publications, that I first-authored, are not focus on the topic of decadal variability and predictability, to further demonstrate my research versatility.

Impact of Arctic climate change on the AMOC:

- **Sévellec, F.**, A. V. Fedorov and W. Liu, 2017: Arctic sea ice decline weakens the Atlantic Meridional Overturning Circulation, *Nature Climate Change*, 7, 604-610.

Expected statistics of hiatus for the 21st century:

- **Sévellec, F.**, B. Sinha and N. Skliris, 2016: The rogue nature of hiatuses in a global warming climate, *Geophys. Res. Lett.*, 43, 8169-8177.

Millennial AMOC variability during glacial-interglacial cycle :

- **Sévellec, F.** and A. V. Fedorov, 2015: Unstable AMOC during Glacial Intervals and Millennial Variability: the Role of Mean Sea Ice Extent, *Earth and Planetary Science Letters*, 429, 60-68.

Indirect observations of vertical velocities in the Southern Ocean :

- **Sévellec, F.**, A. C. Naveira Garraato, J. A. Brearley, and K. L. Sheen 2015: Vertical flow in the Southern Ocean estimated from individual moorings, *J. Phys. Oceanogr.*, 45, 2209-2220.

Theory for 12-hr intense variations of the AMOC:

- **Sévellec, F.**, J. J.-M. Hirschi and A. T. Blaker, 2013: On the near-inertial resonance of the Atlantic meridional overturning circulation, *J. Phys. Oceanogr.*, 43, 2661-267.

