Ocean Model Uncertainty in Climate Prediction

Laure Zanna

Atmospheric, Oceanic and Planetary Physics, University of Oxford, OX1 3PU E-mail: zanna@atm.ox.ac.uk

1 Introduction

Numerical simulations are showing that land warming over the past fifty years occurred largely in response to an overall warming of the oceans rather than as a direct response to increasing greenhouse gases concentration over land (Compo and Sardeshmukh, 2009). Hydrodynamic-radiative teleconnections led to moistening and warming of the air over land and increase of the downward longwave radiation at the surface. Needless to say that the oceans may themselves have warmed from a combination of natural and anthropogenic influences but this mere fact addresses the crucial role of the ocean dynamics and thermodynamics in future climate projections.

The ocean is effectively forced at the surface by momentum, heat, and freshwater fluxes, on a wide range of temporal and spatial scales, while energy dissipation occurs at molecular scales in short and abrupt bursts. The relationship between the large scale circulation and small scale mixing is a consequence of the nonlinear turbulent nature of the ocean, with energy exchanged among all scales. Numerical climate models are based on such well-established physical principles. They have demonstrated to properly reproduce many observed features of the climate therefore enhancing the confidence in model estimates of climate projections.

Despite recent improvements in climate modelling, small and fast unresolved physical processes still introduce large model errors. Model error in climate models can be either be systematic or random and manifest itself in different ways such as a lack of internal variability, underestimates of the frequency of storms or errors in mean temperature. Systematic errors are associated with the model framework and the parametrization choices, while random errors are associated with unrepresented statistical fluctuations in sub-grid physical processes (e.g. convection or mixing).

2 Model errors in ocean components

Figure 1 shows the typical error of zonally averaged annual mean ocean temperature, between climate models from the Intergovernmental Panel on Climate Change (IPCC) and observations, which reaches several degrees in certain regions of the ocean (Solomon et al., 2007).

A poor representation of the thermodynamical and dynamical ocean properties lead to a poor representation of the mean state of the climate (e.g., Fig. 1) and its variability. For example, let us consider the Atlantic meridional overturning circulation (MOC) at 30N (defined as the zonally averaged streamfunction), often used to describe the overall circulation and the transport of heat and salt from low to high-latitudes. The spread between the different IPCC models in their the mean value of the MOC and variability is quite large (Fig. 1) and often outside of the observational estimates available for the 20th century. The spread in the mean state and variability is translated in an even larger spread in the future estimates of the MOC during the 21st century. The poor representation of oceanic processes has obvious implications and consequences. It decreases the reliability of current and future estimates of

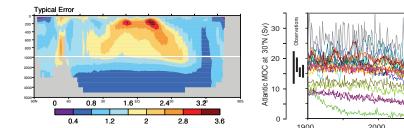


Figure 1: Left: Root-mean-square model error of annual mean temperature climatology over the period 1957-1990, zonally averaged over all ocean basins (in $^{\circ}$ C). The typical error, based on all available IPCC model simulations, is plotted as function of depth and latitude. Right: Evolution of the Atlantic meridional overturning circulation (MOC) at 30N using a suite of coupled climate models under the SRES A1B emissions scenario for 1999 to 2100. Some of the models continue the integration to year 2200 with the forcing held constant at the values of year 2100. Observationally based estimates of late-20th century MOC are shown as vertical bars on the left (Solomon et al., 2007).

natural- and human-induced climate change given that any analysis is affected by the large model errors. Information can undoubtedly be inferred from the output of the different models - though multi-model comparison but these inference can be limited. Another path to provide useful estimates and spread in projections can be obtained from perturbed parameter ensembles (e.g., Tett et al., 1999) however structural uncertainties are not properly account for. Either with multi-model ensembles or perturbed-parameters ensembles, it is extremely difficult to properly account for all model errors and understand causes of errors and associated mechanisms.

3 Singular Vectors in ocean models for climate predictions

Similarly to numerical weather prediction (NWP) and El Niño/Southern Oscillation (ENSO) prediction, the decadal prediction community is interested in making forecasts of different quantities such as regional sea surface temperatures, surface air temperatures or the strength of the MOC. In addition to providing forecasts, it is necessary to provide reliable uncertainty estimates and even more important to understand the deficiencies of our observational system and various models. Singular vectors have been extremely useful in the NWP community to sample errors in initial conditions and have been proven quite informative in interannual and decadal predictions as well.

Estimates of singular vectors in the GFDL coupled atmosphere-ocean general circulation model CM2.1 (Delworth et al., 2006) used in the IPCC can inform us on the predictability of the MOC for example. Using the GFDL CM2.1 (Fig. 2), the growth of temperature, salinity and MOC anomalies are studied in details in Tziperman et al. (2008). A few steps are required to approximate the singular vectors of a coupled climate model, especially if the tangent linear and adjoint models are not available as it is the case for GFDL CM2.1. First, a reduced space based on empirical orthogonal functions (EOFs) of temperature and salinity anomaly fields in the North Atlantic from the output of the control run of GFDL CM2.1 is constructed. Second, under the assumption that the dynamics of this reduced space is linear, the propagator of the system is evaluated and the singular vectors of domain integrated energy and MOC are computed. The singular vectors can growth significantly over a period of 5 to 10 yr (Fig. 2), providing an estimate of the predictability time of the North Atlantic ocean circulation in this model. Obviously, the results are merely an upper bound on the predictability in this GCM. The methodology presented may be used to produce initial perturbations to the ocean state that may result in a stricter estimate of ocean predictability than the common procedure of initializing with an identical ocean state and a perturbed atmosphere. Moreover, the spatial structure of the leading singular vectors in this model, shown in Fig. 3, indicates a large sensitivity to anomalies at high latitudes especially at the boundary between the subtropical and subpolar gyres and in the subpolar gyre.

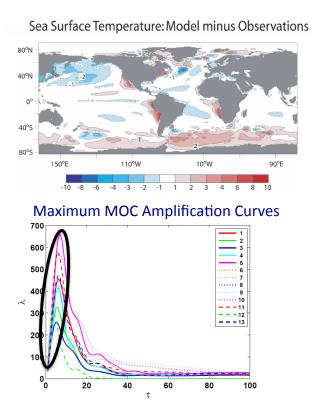


Figure 2: Left: Sea surface temperature: model (GFDL CM2.1) minus observations; Right: Maximum amplification curves. See Tziperman et al. (2008) for further details.

While the computation of the singular vectors in a complex climate model can be useful to estimate initial uncertainties in the model, the analysis remains extremely difficult. Therefore it might be recommended to turn to idealized models to further investigate error growth in ocean models for decadal predictions.

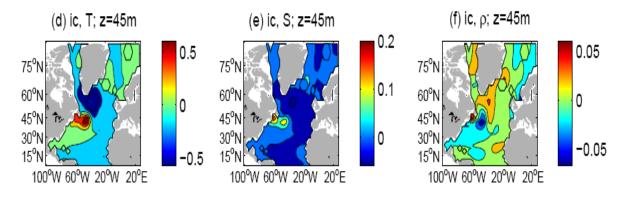


Figure 3: Leading SV of temperature (left), salinity (middle) and density (right).

The limits of predictability of the MOC and upper ocean temperatures due to errors in ocean initial conditions and model parametrizations are investigated in an idealized configuration of the ocean MIT general circulation model (MITgcm; Marshall et al., 1997a,b) shown in Fig. 4. The optimal three-dimensional spatial structures of temperature and salinity perturbations, defined as the leading singular vectors and generating the maximum amplification of MOC and upper ocean temperature anomalies, are evaluated using tangent linear and adjoint models.

A large amplification of MOC anomalies, mostly due to the interference of stable nonnormal modes, is initiated by the optimal perturbations. The largest amplification of MOC anomalies, found to be

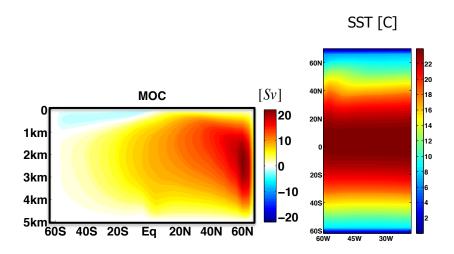


Figure 4: Mean state: (left) MOC mean flow and (right) SST.

excited by high-latitude deep density perturbations in the northern part of the basin especially at the boundary between the two gyres and in the subpolar gyre, is achieved after about 7.5 years (Fig. 5). The anomalies grow as a result of a conversion of mean available potential energy into potential and kinetic energy of the perturbations, reminiscent of baroclinic instability. The time scale of growth of MOC anomalies can be understood by examining the time evolution of deep zonal density gradients, which are related to the MOC via the thermal wind relation. The velocity of propagation of the density anomalies, found to depend on the horizontal component of the mean flow velocity and the mean density gradient, determines the growth time scale of the MOC anomalies and therefore provides an upper bound on the MOC predictability time (Zanna et al., 2011a).

If the singular vectors are constrained to the upper ocean, the maximum growth is found at about 18.5 years. This timescale of 18.5 years is longer than the 7.5 years obtained when the perturbations are allowed over the entire ocean depth. This result implies that the predictability timescales of 10 to 20 years obtained when only atmospheric perturbations are used to initialize ensemble experiments (e.g., Griffies and Bryan, 1997; Pohlmann et al., 2004) may be overestimates. In addition to the difference in growth timescales, the MOC anomaly appears to be less sensitive to upper ocean perturbations than to deeper ones. We find here that a density perturbation of 0.02 kg/m³ in the upper ocean leads to an MOC anomaly of 1.7 Sv compared to 2.4 Sv when the anomalies are mostly located in the deep ocean (Zanna et al., 2011b).

The results suggest that the non-normal linearized ocean dynamics can give rise to enhanced MOC variability if, for instance, overflows, eddies, and/or deep convection can excite high-latitude density anomalies in the ocean interior with a structure resembling that of the singular vectors found. The findings also indicate that errors in ocean initial conditions or in model parameterizations or processes, particularly at depth, may significantly reduce the Atlantic ocean circulation and climate predictability time to less than a decade.

4 Model resolution & the need for new parametrizations

Dynamical processes such as eddies, mixing and convection are crucial for climate as they impact the large-scale ocean circulation and uptake of tracers (temperature and carbon). Many of these processes are excited at the ocean surface (especially at high latitudes), at the interface between the oceanic reservoir of heat, carbon and freshwater and the overlying atmosphere. To illustrate the energetic behaviour of the upper ocean, Fig. 6 shows the sea level height in a $1/10^{\circ}$ horizontal resolution ocean model (Zhai,

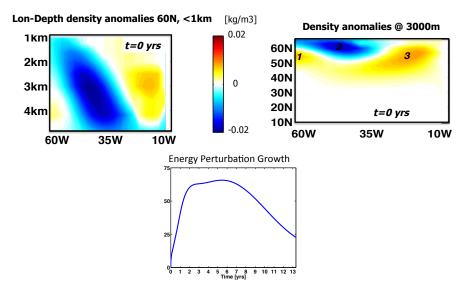


Figure 5: Leading singular vector: (left) longitude-Depth cross section of density at 60N; (right) longitude-latitude of density at 3km-depth. (Bottom) Energy perturbation growth excited by the leading singular vector.

personal communication).

Ocean models used for climate studies and predictions typically have a horizontal resolution of about hundred kms. Therefore mesoscale and sub-mesoscale variability (eddies, turbulent mixing, internal waves and convection) are sub-grid scale and must be parameterized. As previously mentioned, the major source of model error is due to the imperfect or missing parameterizations of unresolved processes.

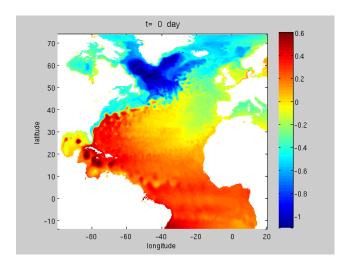


Figure 6: Sea surface elevation from an eddy-resolving model with 1/10 degree horizontal resolution.

Mesoscale eddies in the ocean interior are quasi-adiabatic and therefore their effect should be represented as an eddy-induced velocity, which is the core of the Gent-McWilliams parametrization (Gent and McWilliams, 1990, GM). GM is now the standard parametrization in coupled climate models for interior ocean eddies. However upper ocean eddies have rather different dynamical properties, mesoscale eddies (50 km scale) generated through baroclinic instability of the full water column and submesoscale eddies (1 km scale) generated through ageostrophic baroclinic instabilities within the boundary layer. Currently parametrizations of upper ocean eddies are lacking in coupled climate models used in climate predictions, though a few recent attempts have been made recently in idealized models. Fox-Kemper et al. (2008) show that errors in upper ocean heat transport at high latitudes in the Southern Ocean can be dramatically reduced by introducing the parametrized effects of the mesoscale eddies. Furthermore,

the mixed layer depth can be improved by including the effect of submesoscale eddies, which involves slumping fronts restratifying the boundary layer. Dynamical effects from upper ocean eddies have a substantial impact on boundary layer and therefore on sea-surface temperatures, mixed layer depth, heat uptake which are key quantities for climate variability on timescales from days to decades and beyond.

5 Conclusions and Future directions

While the effects of anthropogenically-forced climate change are expected to continue, future regional changes on timescales of a few years to decades ahead will also be strongly influenced by natural climate fluctuations. Understanding and modelling these variations remains a challenge and unresolved ocean processes in climate models can be the cause of large model uncertainties in the predictions. Despite a few recent improvements described in the previous sections, parametrizations of unresolved ocean processes remain of utmost interest and difficulty. The development of unconventional (e.g. stochastic) parametrizations should therefore be addressed.

Given that the fast and small-scale processes set the properties of the mean climate and participate in exciting variability, it should be interesting to explore how the different parametrizations of ocean mixed-layer and convection affect the mean state and variability in climate models. Several interesting regions could be explored, especially the Atlantic and the Southern oceans due to the important role of the overturning circulation and its potential role in climate with interannual to decadal variations modulating the global mean temperature.

Studies using low-order idealized climate models have shown the benefits of stochastic noise on the representation of the climate. Stochastic forcing can excite variability on all timescales (Perez et al., 2005; Saravanan and Mcwilliams, 1997; Alley et al., 2001; Zanna and Tziperman, 2008). For example, the addition of surface atmospheric stochastic noise can explain and reproduce the irregularity of ENSO and its amplitude, which purely deterministic models are incapable of.

Incorporating stochastic physics and parametrizations in ocean models could potentially improve the representation of the climate system in numerical models and provide reliable climate change projections and accurate estimates of uncertainties associated with the projections due to model errors. Stochastic parameterizations have the potential to reduce model error, they can change the mean and variance of a probability distribution function.

A few studies have investigated the potential of the ocean mesoscale eddy field to be properly represented by a stochastic process in idealized ocean models (Berloff, 2005) however this area is still largely under studied. Over the past year, many physical oceanographers have slowly built upon the knowledge developed by the atmospheric community regarding stochastic parametrizations. Several groups are now conducting research in developing stochastic parametrizations of ocean processes and introducing stochastic physics in the ocean component of coupled models for predictions.

Bridging the gap between observations, theory and modeling is crucial. Ocean observations are becoming more dense (both in space and time). Proper analysis of this data is needed but more importantly linking the newly available data to theory, in search for new parametrizations and also to test, validate and constrain our models. For example, ocean heat content, ARGO and altimetry could be used to reduced model uncertainties to increasing CO2, especially on regional scales. Moreover, regional and global statistical models based on observations could be used as benchmarks for IPCC models, both to test that the models capture the correct properties but also demonstrate the appropriate skill (Zanna, 2011).

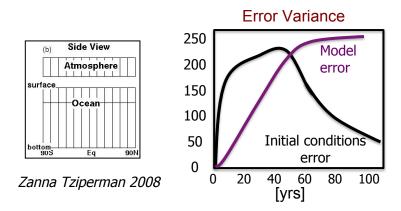


Figure 7: Error variance: model error (as a stochastic term) and initial condition error in an idealized coupled box model.

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