Model uncertainties in climate prediction: Don’t forget the oceans!

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Outline

- Role of ocean in recent continental warming
- Examples of uncertainties & errors in ocean models
- Recent studies dealing with uncertainties, high-latitudes processes
- Possible Future directions: Observations to reduce uncertainties, Stochastic physics

→ not enough to rely on global climate models, stronger links between theory/obs and modeling centers
Continental warming influenced by ocean temperatures


a Forced with observed SST changes


a Observed (blend of multiple datasets)

C Forced with observed SST and CO₂ changes

d Forced with observed SST, CO₂, and other forcings

Surface & ocean interior properties are important including circulation
Multi-model Error in Temperature

Zonal Mean global ocean potential temperature difference (C)

(IPPC AR4, Ch.8 supp)
Climate Projections

• Multi-Model, AR4

• Climateprediction.net ensemble (~700 members) with FAMOUS (Yamazaki et al)

• Seven CO2 emission scenarios

• Not easy to understand the behavior of the models and uncertainties
Singular Vectors in IPCC AR4 model

- 1000 years of control run from GFDL CM2.1
- North Atlantic annually averaged temperature and salinity fields
- Reduced space based on EOFs

**GFDL CM2.1**

(Delworth 2006; Delworth et al. 2006; Gnanadesikan et al. 2006; Griffies & Coauthors 2005; Stouffer et al. 2006; Wittenberg et al. 2006)
SVs to detect most sensitive regions

Maximum MOC Amplification Curves

- Maximum growth of energy and MOC 5-8 yrs
  Can be used to sample uncertainties
  
  \textit{(Tziperman, Zanna \& Penland 2008)}

- Build on reduced space; the SVs could potentially project on higher order EOFs \textit{(Similar analysis in HadCM3, Hawkins \& Sutton, 2009)}

- Can be used to initialize climate predictions
SVs in idealized ocean MITgcm

Primitive equations, 1°x1°, 15 Levels, Annual averaged Wind & Buoyancy forcing (Marshall et al, 1996)
SVDs in idealized ocean MITgcm

(Zanna et al 2011)

- **Growth** → conversion of mean available potential energy into perturbation kinetic and potential energy

- Perturbations “leaning” against the mean flow (~baroclinic instability)
Leading 3D Singular Vector

- largest sensitivity of MOC’ to perturbations at depth & high-latitudes

- Perturbation estimate: \( \bar{P}_0 = 0.1C \rightarrow MOC'(7.5\text{ yrs}) = 2.4\text{ Sv} \ (12\% \ mean) \)

- Errors at high latitudes, at depth in ocean i.c. & model representation (overflows, eddies, deep convection) limit predictability; large impact on the ocean and climate

- Additional observations and better parameterizations are necessary
High-latitudes ocean processes are important for climate

- Upper ocean dynamics = communication between the atmosphere & the oceanic reservoir of heat, freshwater & CO2

- Small-scale & local processes impact the large-scale ocean circulation and uptake of tracers (temperature + carbon)

- Mesoscale & microscale variability (turbulent mixing due to breaking internal waves & convection) are sub-grid scale & are parameterized; most models have similar parameterizations

- Examples of new parameterizations for deep convection and eddy-mixed layer
Deep convection: role in global ocean circulation & heat and carbon uptake

Difference between Hydrostatic and Non-hydrostatic

Temperature

Tracer

The computational cost of the SP approach is significantly less than that of a full 3-d NH model. Moreover the independent 2-d plume models provide a rich source of parallelism. The scheme outlined here could prove beneficial to emerging petascale ocean applications which are targeting basin and global scale simulation at a few kilometer resolution. Embedding a 2-d non-hydrostatic special purpose model in such integrations would provide a computationally tractable way to incorporate non-hydrostatic effects in the relatively near future.

The recipe we have outlined should also apply to other processes where there is a relatively clean separation of scales and where approximate parameterizations are currently employed. For example, various
Open Ocean Deep Convection

Super-parameterization
(Campin et al 2010)

(Atmospheric super-parameterizations; Grabowski, 2001, Khairoutdinov et al., 2005, 2008; Wyant et al., 2006; Grabowski, 2006; Majda, 2007; Tao et al., 2009)
Open Ocean Deep Convection

Super-parameterization - Non-hydrostatic

Hydrostatic - Non-hydrostatic

(Astronomical super-parameterizations; Grabowski, 2001, Khairoutdinov et al., 2005, 2008; Wyant et al., 2006; Grabowski, 2006; Majda, 2007; Tao et al., 2009)
Sea level height – $1/10^\circ$ eddy resolving simulation

Courtesy Xiaoming Zhai
Eddy-Mixed Layer Interactions

- Mesoscale eddies: Ocean interior = Gent-McWilliams parameterization (adiabatic eddy-induced velocity); Turbulent BL = eddy induced velocity with zero shear (well-mixed BL models) + an along-boundary down-gradient flux of density (diabatic mesoscale eddies in the BL)  
  Fox-Kemper et al 2010

zonally averaged heat flux across 47°S

- control run with GM
- run with new parameterization
- 1/8° global eddy resolving simulation
Eddy-Mixed Layer Interactions

- Submesoscale eddies: buoyancy gradient & front development

Mixed layer depth changes after 10 yrs between control run & run with submesoscale restratification

Ferrari et al 2008
Future Directions

- Using observations to constrain & test the models especially on regional scales

- Stochastic physics in ocean models

- Linking theory/obs /idealized studies with global climate models is crucial
Using observations to reducing uncertainties

- Ocean heat content, ARGO & altimetry: large uncertainties with obs, analysis & models; can be used to reduced model uncertainties to increasing CO2

- Regional statistical models based on observations can be used as benchmark for IPCC models

Annual averaged
Atlantic SSTs, maximum amplification curves
(Zanna 2011)
Role of Stochasticity

- Stochastic Physics in simple model of the ocean circulation

- Stochastic parameterization: turbulent mixing & convection

- Implementation of stochastic physics in ocean models and coupled ensemble data assimilation