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Predicting the Future Trajectory of Arctic Sea Ice:

Reducing Uncertainty in High- Resolution Sea Ice Models

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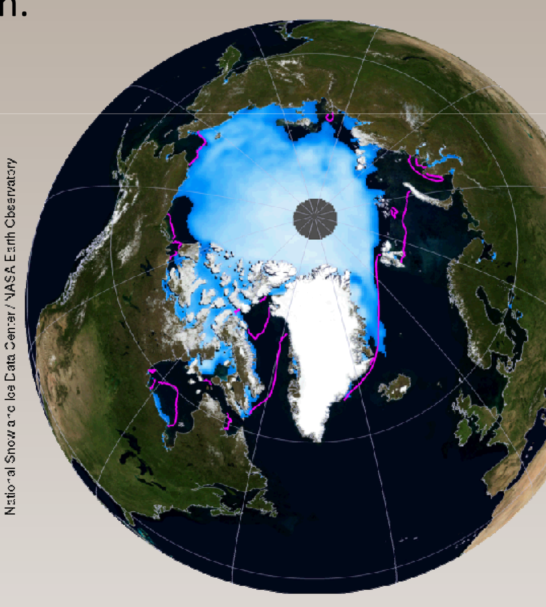
Numerical Analysis and Applications

Introduction

Arctic sea ice is an important component of the global climate system, reflecting a significant amount of solar radiation, insulating the ocean from the atmosphere and influencing ocean circulation by modifying the salinity of the upper ocean.

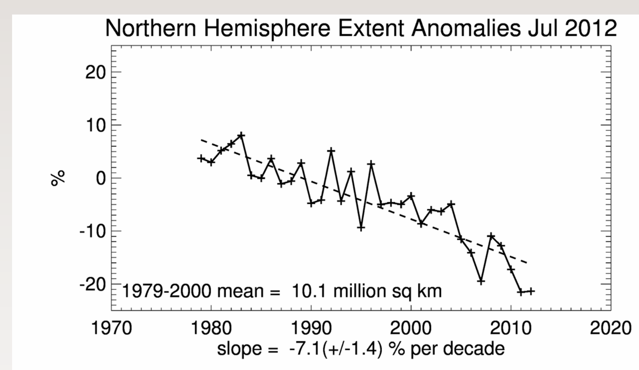
The volume and extent of Arctic sea ice have shown a significant decline in recent decades with implications for global climate as well as regional geopolitics. Increasing interest in exploration and mineral extraction in the Arctic in additional to climate feedback effects make a predictive sea ice modeling a high priority.



Arctic sea ice concentration, July 2012. (NSIDC)

Sea ice models vary in their predictions for Arctic sea ice evolution, but all have underestimated the rate of decline in minimum sea ice extent over the last thirty years [1]. Comparisons with satellite data also show that sea ice models do not accurately reproduce the thickness decline or observed drift and deformation patterns [2].

The models contain many physical parameters with values that are inherently uncertain. A robust, predictive sea ice modeling capability requires an understanding of how these uncertainties are propagated by different numerical algorithms, discovery of the most important physical parameters in the models, and a consistent approach for comparative evaluation of the each model.



Arctic sea ice concentration, July 1979-2012. (NSIDC)

Sea Ice Models

For this evaluation, the state-of-the-art LANL CICE model [3] has been used. Physical processes included in this model are motion and deformation due to surface winds and ocean currents, variations in thickness including leads (open water) and ridges, and the annual cycle of growth and melt due to radiative forcing.

These processes are modeled mathematically with

- 2-d momentum equation for ice velocity

$$\rho \bar{h}\frac{d\mathbf{v}}{dt} = \mathbf{t}_a + \mathbf{t}_w - f_c + \nabla\cdot\bar{h}\sigma$$

- Ice thickness distribution evolution equation

$$\frac{dg}{dt} + (\nabla\cdot\mathbf{v})g + \frac{\partial(fg)}{\partial h} = \psi$$

- 1-d heat equation for temperature and change in thickness

$$\rho c\frac{dT}{dt} = \frac{\partial}{\partial z}\left(k\frac{\partial T}{\partial z}\right) + \kappa I_0 e^{-\kappa z}$$

ρ = ice density
$\bar{h}$ = ave. thickness
$\mathbf{v}$ = ice velocity
$\mathbf{t}_a$ = atmospheric drag
$\mathbf{t}_w$ = ocean drag
f_c = Coriolis force
σ = ice stress tensor
g = ice thickness distribution
$f = \partial h/\partial t$
ψ = ridging function
T = ice temperature
c = heat capacity
k = conductivity
κ = extinction coefficient

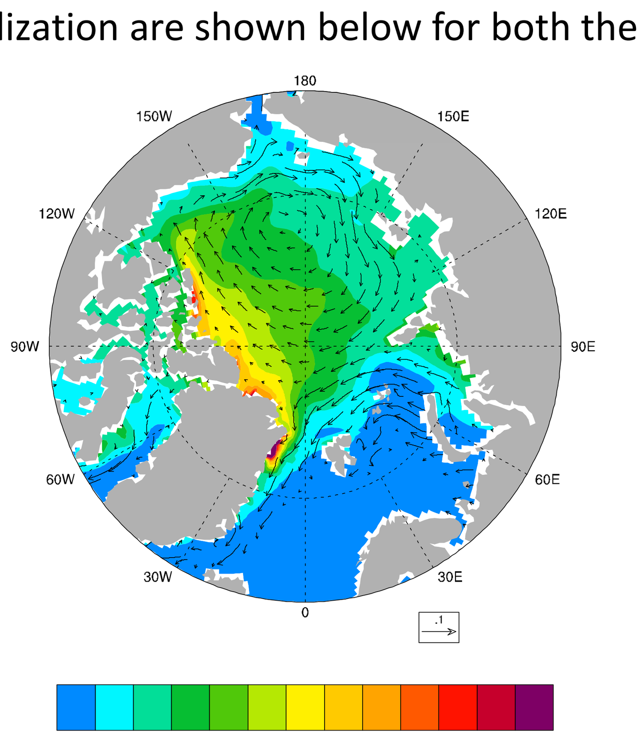
In addition to these equations, there are sub-models for various components such as ridging function, ice stress, and even conductivity. This creates a complex chain of interactions with many variable parameters.

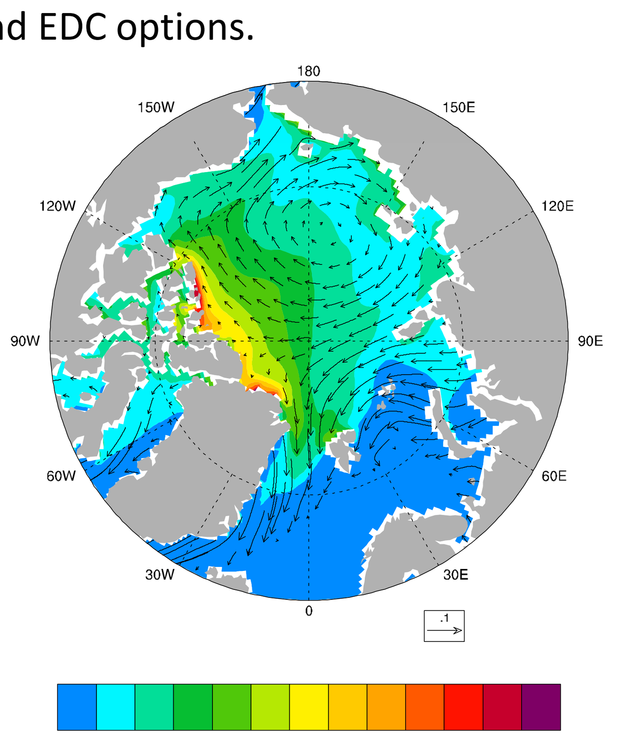
Anisotropic Rheology

One sub-model with important effects on the velocity and deformation is the rheology used to compute ice stress. The default rheology in the LANL CICE model is the elastic-viscous-plastic (EVP) rheology. This model assumes that cracks are distributed randomly throughout the ice and they result in a form of isotropic weakening. This assumption does not hold for high resolutions where a single large crack may be associated with strong localized deformation.

An alternative formation will some potential to improve sea ice models has been developed by Schreyer et al. [4]. In this elastic-decohesive (EDC) rheology cracks are explicitly modeled as displacement discontinuities and intact ice modeled as elastic. As cracks form the ice weakens in preferential directions resulting in anisotropic behavior.

The EDC model has been implemented in the LANL CICE code for the sensitivity, model selection and uncertainty analyses. Thickness and velocity results from a single year run with initialization are shown below for both the EVP and EDC options.



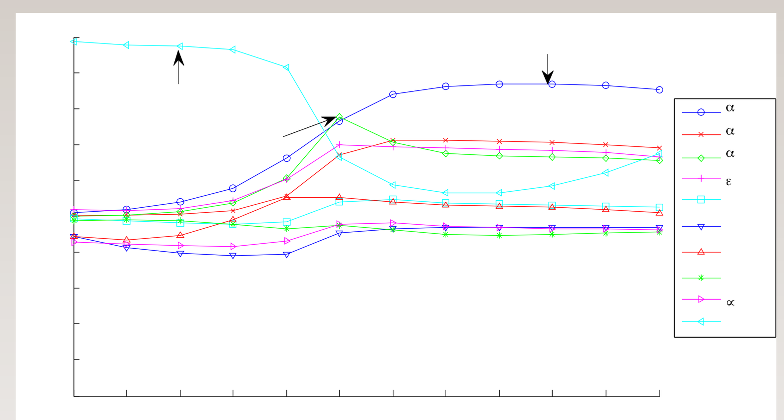


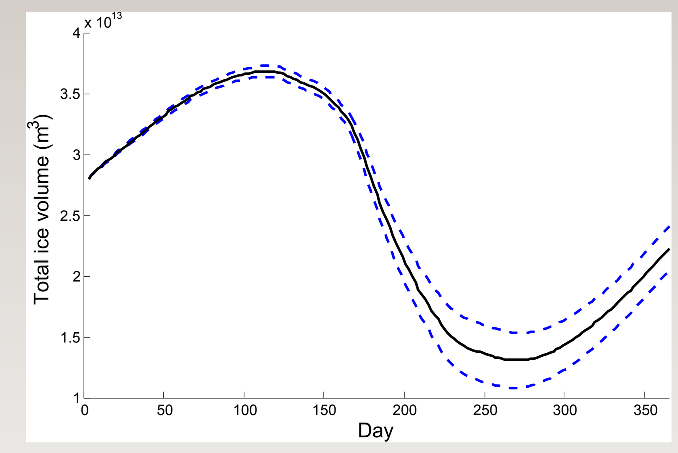
Ice thickness contours and velocity vectors after a single year run of CICE on a 1 degree grid with the EDC (left) and EVP (right) rheologies.

Sensitivity Analysis

Our sensitivity analysis builds on previous work where six response functions, which include ice volume, ice area, ice extent, root mean square ice speed, and central Arctic ice thickness and speed, were evaluated with respect to a combination of ten model parameters [5]. The DAKOTA framework [6] is used to vary parameters simultaneously using Latin hypercube sampling (LHS) and standardized regression coefficients are computed using a linear regression model to quantify the effects of the different parameters.

In the original analysis a set of ten, primarily thermodynamic, parameters were assessed for a single year model run. A plot of the standardized regression coefficients for total Arctic ice volume with respect to each of the ten parameters is shown below along with the yearly cycle of ice volume for 50 LHS samples. In this case the fresh ice conductivity and albedo parameters are dominant.





Standardized regression coefficients for a selection of ten parameters for Arctic ice volume (left) and the mean and 2-sigma variations of total ice volume for the single year run (right).

In the current analysis rheological parameters that are specific to the EVP and EDC rheologies are evaluated in a similar manner. A single year run of a 1 degree global CICE simulation is used to evaluate the same set of response functions. The final result will be two sets of parameters that are the most important for the EVP and EDC versions of CICE, respectively.

Parameter Estimation and Model Selection

Given a set of the most important parameters from the sensitivity analysis the best fit parameter values will be estimated. With the DAKOTA framework a nonlinear least-squares approach is used where we seek to minimize the following function

$$S(\theta) = \sum_{i=1}^{n}\left(y_i - f(x_i;\theta)\right)^2$$

for a vector of parameters θ that are inputs to the model f. The responses y are obtained from the data sets listed in Table 1. A 2 year subset of the available data will be used for the parameter estimation.

Table 1: Data for use in parameter estimation and model selection.

Data Type	Temporal Coverage	Source
Ice Concentration/Area	1979-present (monthly)	www. nsidc.org
Ice Thickness	2003-2007	rkwok.jpl.nasa.gov/icesat
Ice Motion	1978-2004	rkwok.jpl.nasa.gov/icemotion
Ice Deformation	1996-2008 (winter months)	www-radar.jpl.nasa.gov/rgps

An initial model selection will be done by computing the objectives $S(\theta)$ for each model configuration using the optimized parameters for a subset of the data not included in the parameter estimation step. In addition, a more sophisticated Bayesian approach as proposed in [7] is being investigated.

Uncertainty Analysis

The final task in this research will be to quantify the uncertainty in the simulations and to determine whether the data actually fall within the model results and uncertainty bounds. For complex models with many sources of uncertainty this can be a difficult task. We will use the method of Romero *et al.* who combine various uncertainty measures for a complex system into uncertainty bounds for a meaningful measure of the overall uncertainty of the system [8].

The final result will be a set of the most important physical parameters along with their optimal values, a ranking of the model configurations, and an estimation of the uncertainty in model responses for ice thickness, extent, and velocity.

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