Quantifying Uncertainties in the Seasonal Cycle of Arctic Sea Ice

Donald D. Lucas[1,*], Curt Covey[1], Richard Klein[1,2], John Tannahill[1], and Detelina Ivanova[1] (* presenting author)

1. Lawrence Livermore National Laboratory, Livermore, CA
2. University of California, Berkeley, CA

AGU Fall Meeting, San Francisco | 9-13 December 2013
LLNL-POST-647375
AGU Abstract GC31B-1044

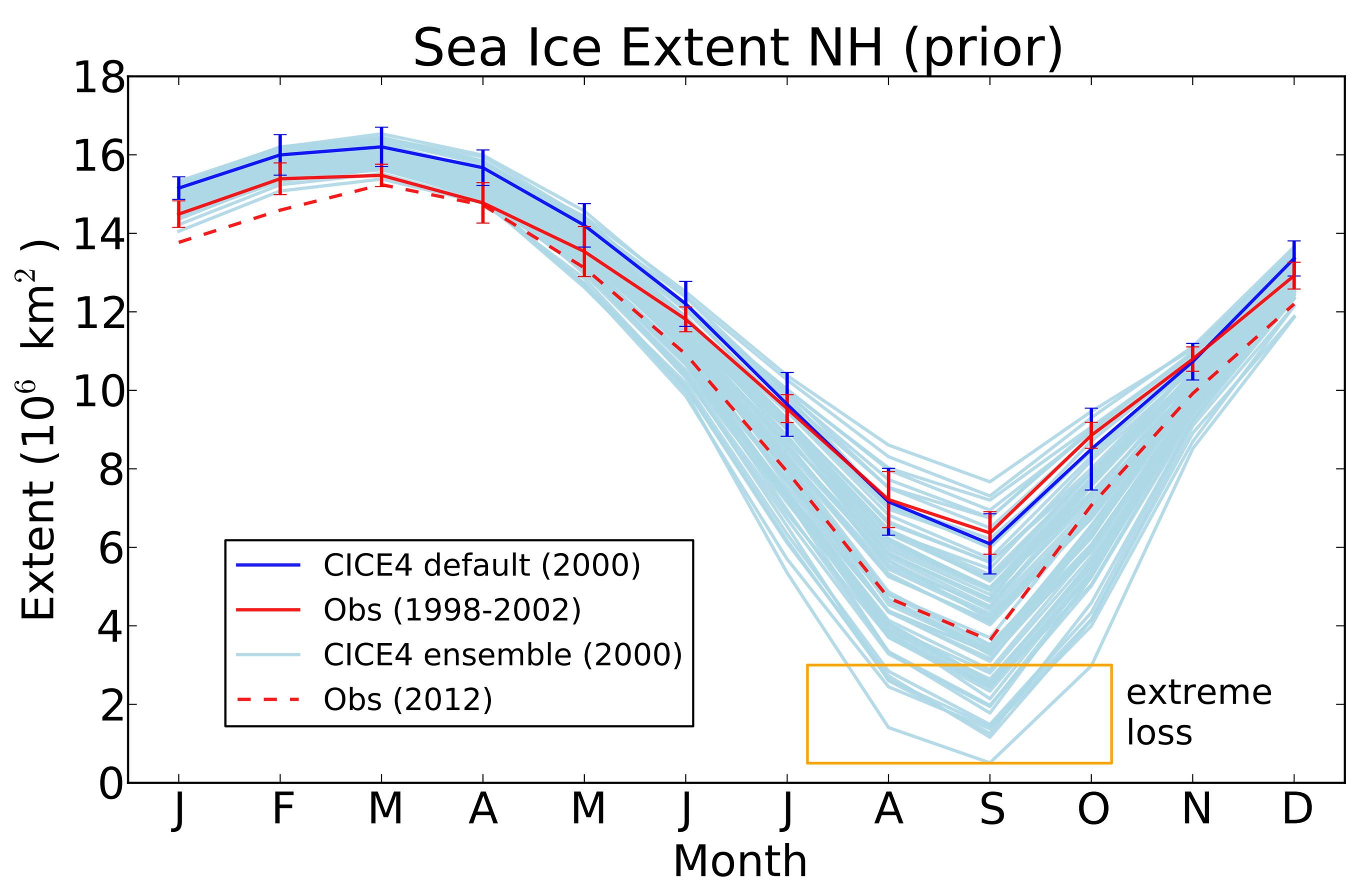
I. Perturbed-Parameter Ensembles of CICE4

- **Motivation** Are uncertainties in sea ice physics parameters in climate models large enough to account for the recent observations of rapid summertime Arctic sea ice loss?
- **Approach** UQ ensembles to sample uncertainties in 7 sea ice physics parameters in the Community Ice CodE version 4.0 (CICE4). [prior ranges provided by Polar Climate Working Group]

Parameter	Description	Low, Def, High
dT_mlt_in	snow melt onset temperature	0.10, 1.5, 1.8
R_ice	ice grain radius tuning parameter	-1.9, 0.0, 1.9
R_pnd	pond grain radius tuning parameter	-1.9, 0.0, 1.9
R_snw	snow grain radius tuning parameter	-1.9, 1.5, 1.9
rsnw_melt_in	snow melt maximum radius	500, 1500, 2000
ksno	thermal conductivity of snow	0.1, 0.3, 0.35
mu_rdg	e-folding scale of ridged ice	3, 4, 5

- **Ensemble design**
  - CAM4+CICE4+CLM+Slab Ocean, compset E_2000 (yr 2000 repeated)
  - CAM4 grid = finite volume f19, CICE4 grid = displaced pole gx1v6
  - 40 year simulations, last 10 years used for analysis
  - 70 Latin hypercube simulations using LLNL's 'UQ Pipeline' workflow

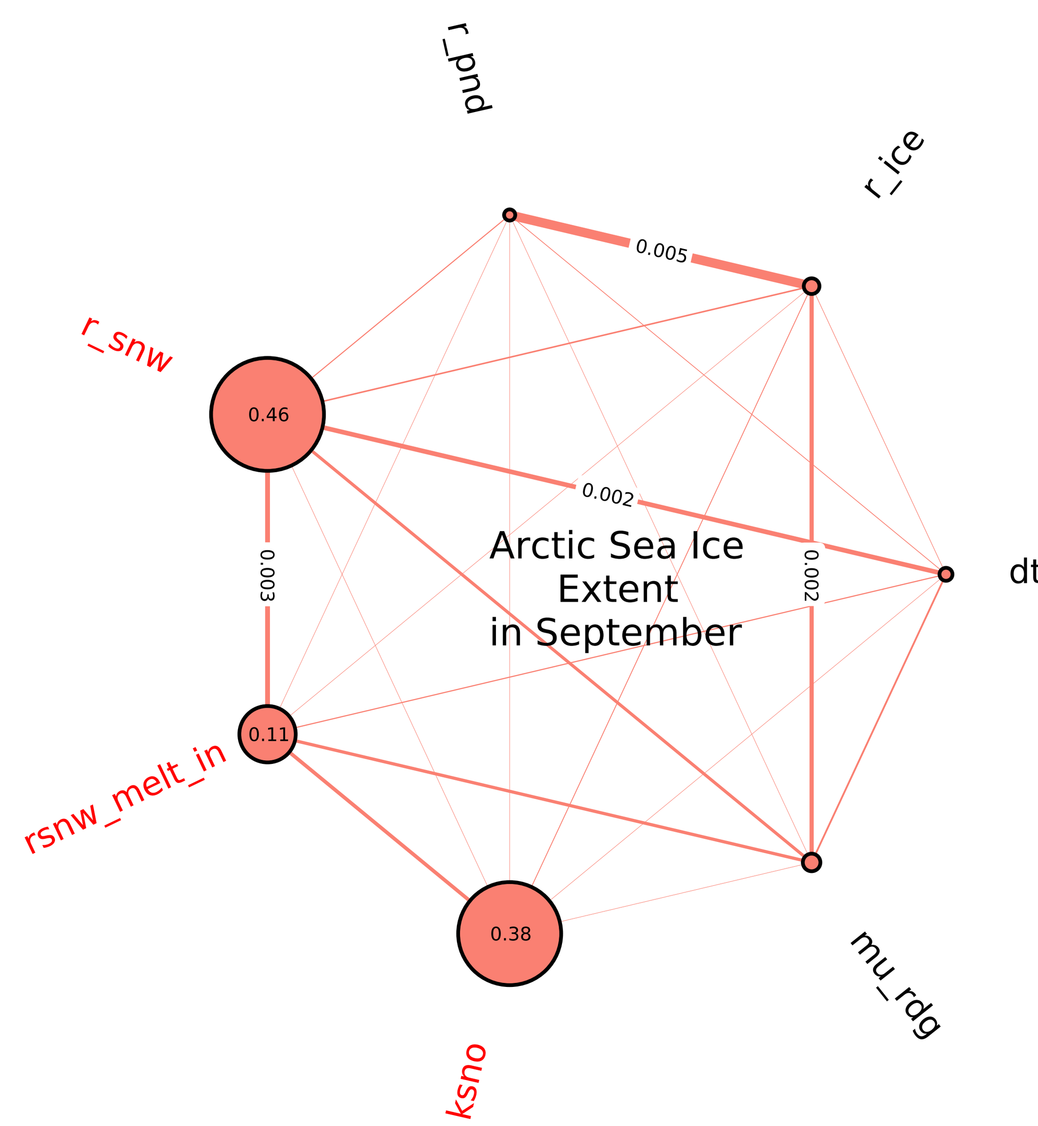
II. Seasonal Cycle of Arctic Sea Ice



Observed and simulated seasonal cycles of Arctic sea ice extent. The default CICE4 cycle (blue) in year 2000 agrees well with observations (solid red, Fetterer et al). Error bars show interannual variability. Observations for 2012 show rapid summertime loss of sea ice (dashed red). Select CICE4 ensemble members (light blue) also exhibit extremely low to ice-free conditions during the summer.

III. Sources of Variability in CICE4 Ensemble

Polynomial chaos is used to decompose the ensemble variability into contributions from individual parameters (nodes) and parameter interactions (edges).



Ensemble Variance Decomposition

$$V_{tot} = \sum_i V_i + \sum_{ij} V_{ij} + \dots$$

$$\text{node}_i \propto V_i / V_{tot}$$

$$\text{edge}_{ij} \propto V_{ij} / V_{tot}$$

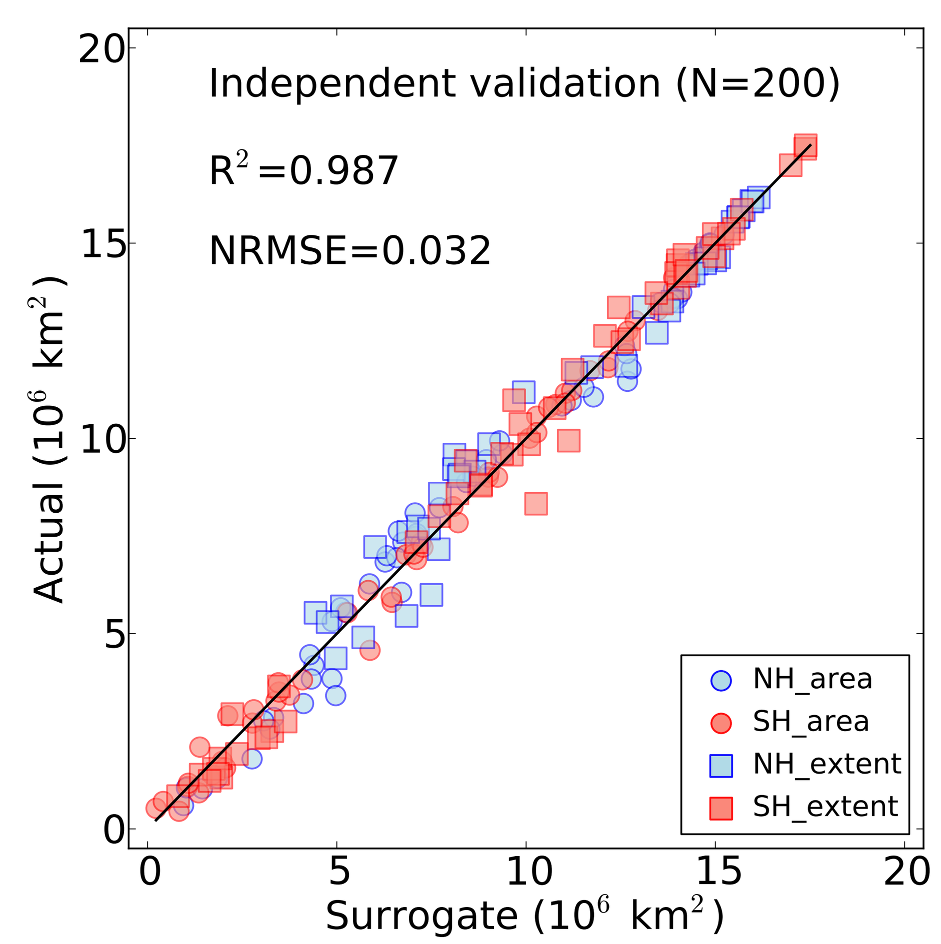
$$\text{edge}_{ijk} \propto V_{ijk} / V_{tot}$$

The 3 parameters **r_snw**, **rsnw_melt_in** and **ksno** are the key drivers of ensemble variability, accounting for most of the variability over the full seasonal cycle.

IV. Machine Learning Surrogate of CICE4

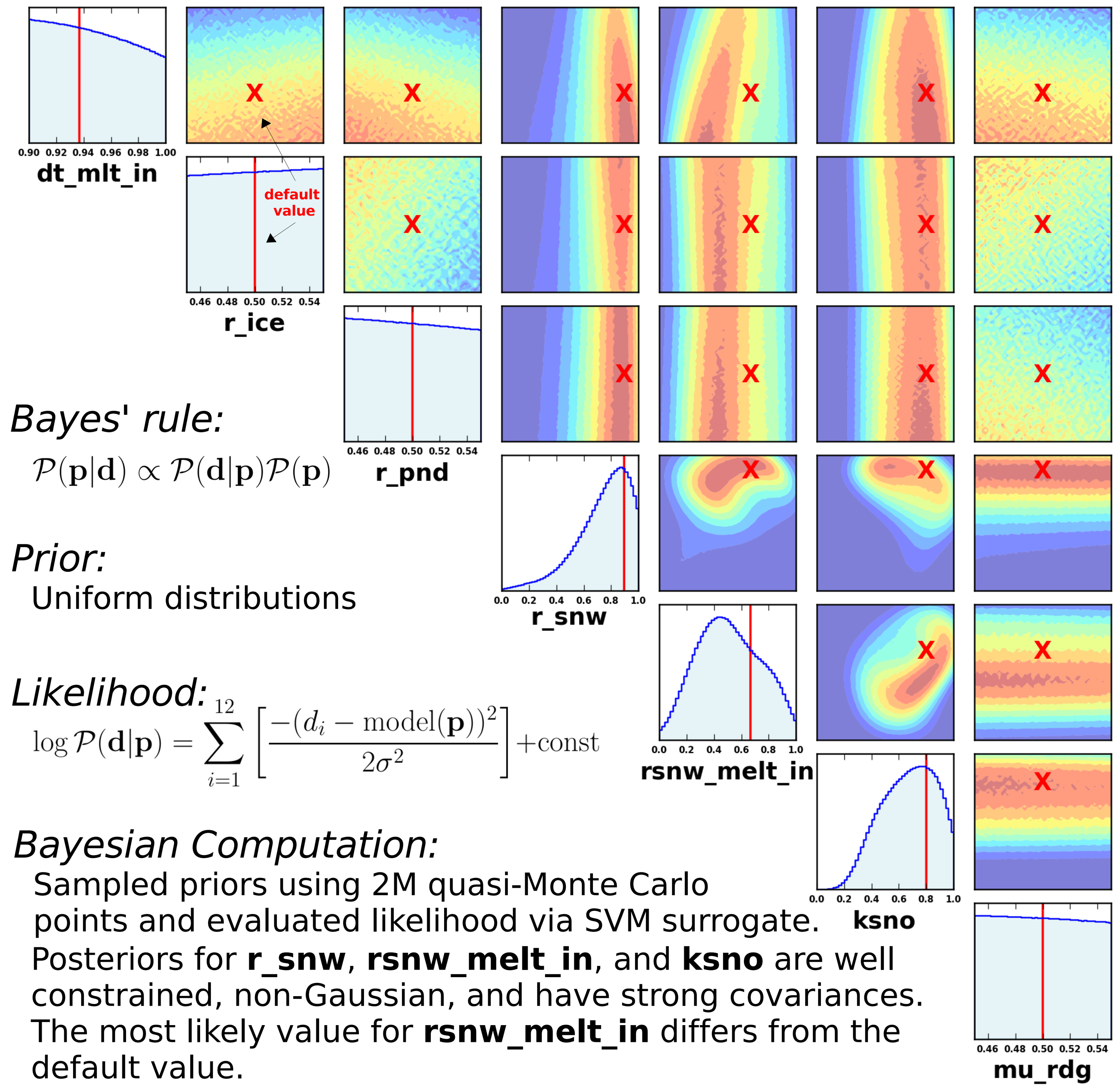
The ensemble is used to train a single *Support Vector Machine* (SVM) to approximate CICE4 output as a function of parameter values, month, hemisphere, and quantity. The computationally-efficient SVM surrogate is used to evaluate millions of versions of CICE4 and make probabilistic comparisons to observations.

CICE4 $\approx$ SVM(p_1, …, p_7, month, hemisphere, extent|area)



V. Bayesian Calibration of CICE4 Parameters

Joint posterior probability distribution of CICE4 parameters



Bayes' rule:

$$\mathcal{P}(\mathbf{p}|\mathbf{d}) \propto \mathcal{P}(\mathbf{d}|\mathbf{p})\mathcal{P}(\mathbf{p})$$

Prior:
Uniform distributions

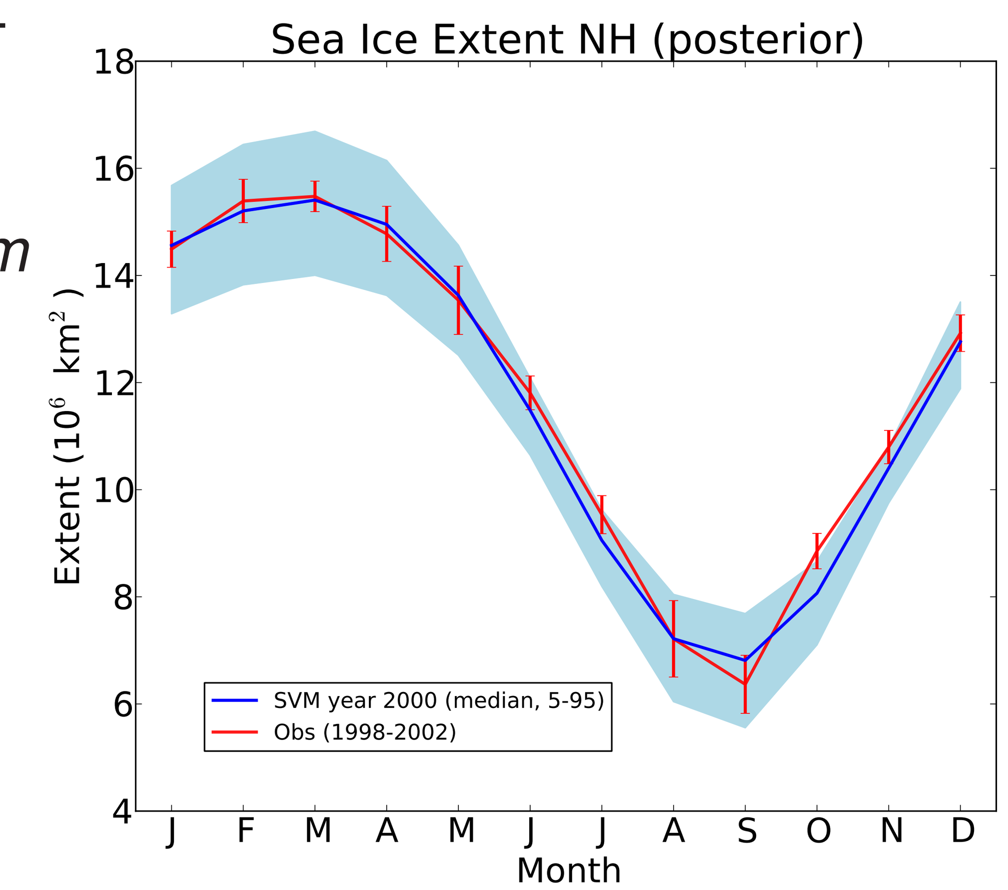
Likelihood:

$$\log \mathcal{P}(\mathbf{d}|\mathbf{p}) = \sum_{i=1}^{12} \left[\frac{-(d_i - \text{model}(\mathbf{p}))^2}{2\sigma^2} \right] + \text{const}$$

Bayesian Computation:
Sampled priors using 2M quasi-Monte Carlo points and evaluated likelihood via SVM surrogate. Posteriors for **r_snw**, **rsnw_melt_in**, and **ksno** are well constrained, non-Gaussian, and have strong covariances. The most likely value for **rsnw_melt_in** differs from the default value.

VI. Impact of Parameter Calibration on CICE4

Samples drawn from posterior PDF for **r_snw**, **rsnw_melt_in**, and **ksno** using a *rejection algorithm* and evaluated with the SVM surrogate. The calibrated model better fits the observations, has an average 5-95% quantile range of 2×10^6 km^2, and has a low probability of ice-free conditions during the summer of 2000.



This work performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344 and was funded by the UQSI LDRD at LLNL (project code 10-SI-013). D.L. also received support from DOE's Office of Science for the SciDAC project on Multiscale Methods for Earth System Models.