Accelerating Earth System Models with machine learning

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Earth system models are our best tools for predicting future climate: that includes temperature, water resources, and extreme events. However, long model runs (1850-2100) take weeks to run on DOE supercomputers. Here, we show examples of how machine learning models can be integrated into existing physics-based models to produce better climate predictions at lower computational costs.

INTEGRATING ML AND PHYSICS MODELS

Clouds

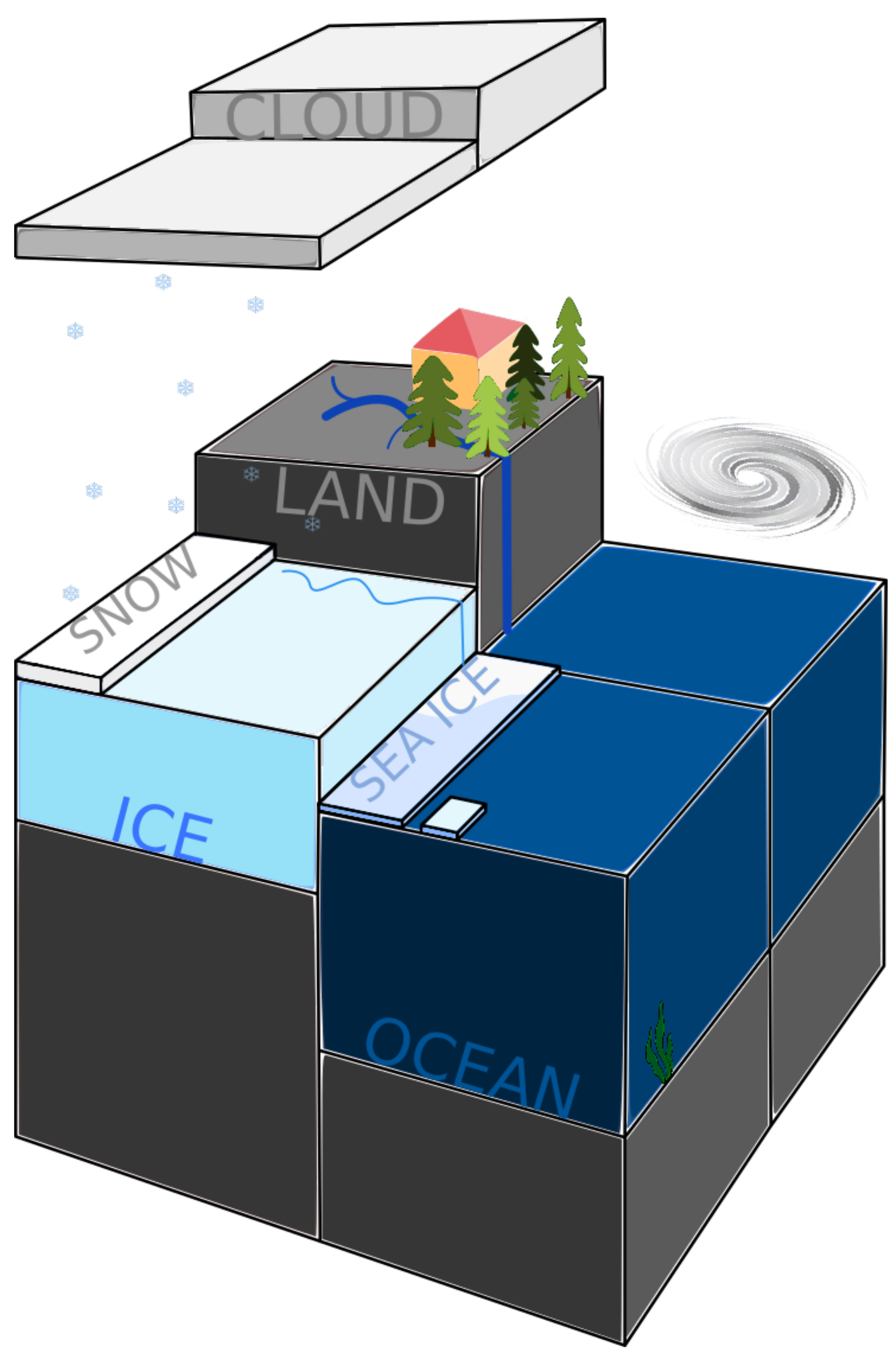
Challenge: Clouds are the biggest source of uncertainty in climate models, but cloud-resolving models are prohibitively expensive

Opportunity: Train deep neural nets to emulate high-resolution cloud models[2]

Extreme events

Challenge: Disaster relief planners need storm and drought forecasts, but Earth system models predict average variables like wind speed and temperature

Opportunity: Build classifiers to identify extreme events within climate model datasets[5]



Ensembles

Challenge: The climate is highly variable, and each model run only captures one of many possible futures

Opportunity: Optimize multi-model predictions using online[1]

Parameterization

Challenge: Earth System Models have many parameters, constrained by various forms of data and inverse modeling

Opportunity: Use machine learning regression to learn parameters from data[7], and to integrate data into simulations[3]

And more:

Climate model super-resolution • Predicting model crashes online • Classifying land and cloud features from satellite imagery[4] • Calibrating satellite observations[3] • Adaptive numerical meshing[8] • Using new polar data

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Tackling Climate Change with Machine Learning

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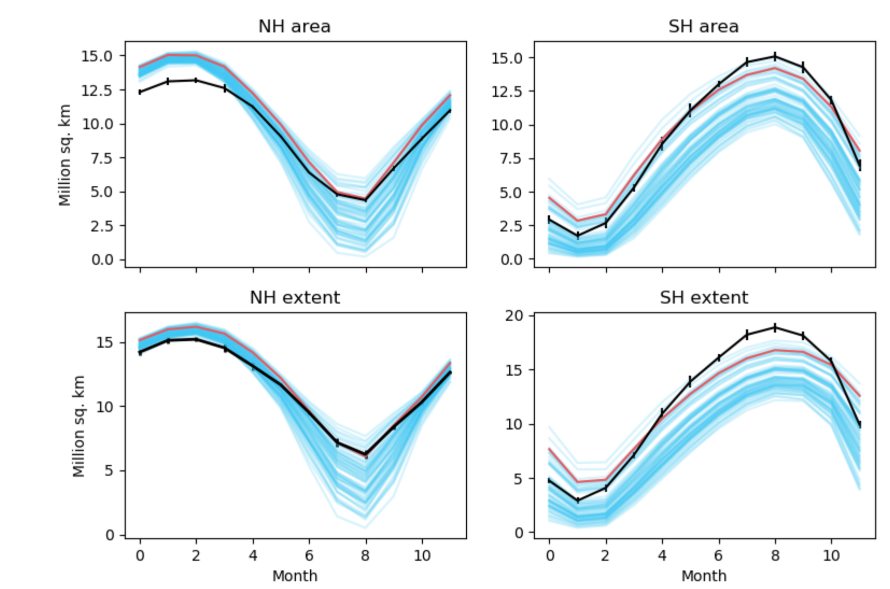
LEARNING SEA ICE MODEL PARAMETERS

Sea ice increases the Earth's reflectivity, and controls warming rates in Arctic and Antarctic ecosystems. Current models, however, over-estimate the loss of Antarctic sea ice cover[9], and under-estimate ice loss in the Arctic[6].

SIMULATED DATA

To explore the sources of uncertainty in CICE, the DOE's leading sea ice model, we identified and perturbed the most uncertain parameters in CICE[10] within a physics-constrained range.

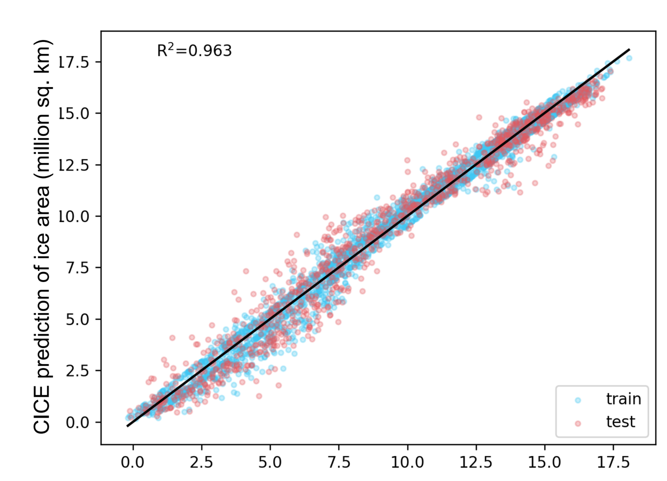
Parameter		Perturbation range
dT_melt_in	Snow melt temperature	0.10 – 1.8 (1.5)
R_ice	Ice grain radius tuning param.	-1.9 – 1.9 (0.0)
R_pnd	Pond grain radius tuning param.	-1.9 – 1.9 (0.0)
R_snw	Snow grain radius tuning param.	-1.9 – 1.9 (1.5)
rsnw_melt_in	Snow melt max. radius	500 – 1500 (1000)
ksno	Snow thermal conductivity	0.1 – 0.35 (0.3)
mu_rdg	Ridged ice folding scale	3 – 5 (4)



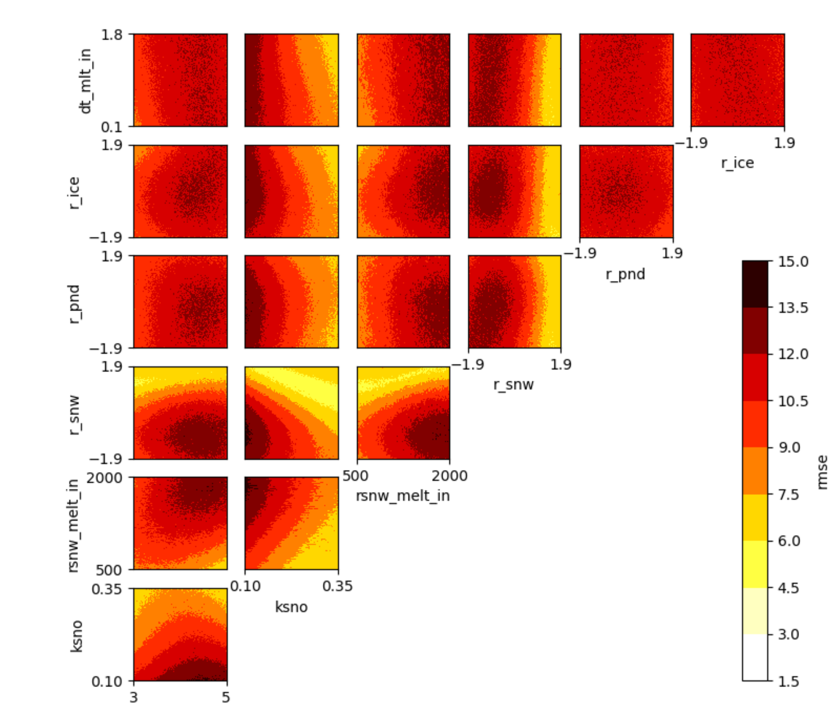
Simulated sea ice area and extent during perturbed parameter runs (N=70, blue) compared to CICE4 results with default values (red) and real data from year 2000 (black). All model runs were driven by a year 2000 atmospheric forcing with CAM4 on a slab ocean.

SURROGATE MODEL

We used the ensemble to train a support vector machine (SVR) that approximates CICE output at ~one ten millionth the computational cost. Using the SVR, we sampled 2 million sets of parameters from a uniform prior distribution and evaluated their fit to the observed data from year 2000.



Above: Comparison of CICE and SVR surrogate predictions.



Right: comparison between SVR prediction and year 2000 data as a function of model parameters. Lower RMSE correlates with higher likelihood. Data points weigh both hemispheres (N and S) both variables (ice extent and area) and all 12 months according to their interannual variability in years 1998-2002.

SEA ICE RESULTS

We find that (1) most physically-reasonable combinations of parameters produce lower sea ice concentrations than the default CICE configuration, which may be favorable for fitting Arctic sea ice data, (2) this configuration of CICE may be successfully approximated with a support vector machine surrogate at a far lower cost, and (3) the most likely values for *ksno* and *r_snw* are higher than the CICE defaults.

Machine learning models may replace expensive parts of Earth System Models at lower cost

REFERENCES

[1]Tracking climate models. Monteleoni et al., 2011.
[2]Could machine learning break the convection parameterization deadlock?. Gentine et al., 2018.
[3]Deep learning and process understanding for data-driven Earth system science. Reichstein et al., 2019.
[4]Deep learning classification of land cover and crop types using remote sensing data. Kussul et al., 2017.
[5]Application of deep convolutional neural networks for detecting extreme weather in climate datasets. Liu et al., 2016.
[6]Arctic sea ice decline: Faster than forecast. Stroeve et al., 2007.
[7]Artificial intelligence in geoscience and remote sensing. Lary, 2009.
[8]A supervised learning framework for arbitrary Langrangian-Eulerian simulations. Jiang et al., 2016.
[9]Observed and simulated changes in Antarctic sea ice extent over the past 50 years. Gagné et al., 2015.
[10]Uncertainty quantification and global sensitivity analysis of the Los Alamos sea ice model. Urrego-Blanco et al., 2016

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