Advancing Sea Ice Predictability in E3SM with Machine Learning

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Focal Area(s)

To improve predictions of sea ice in E3SM we propose to develop a hierarchy of data-driven models using observational and simulation data to investigate the most important Earth system drivers of sea ice variability and loss, develop surrogates that build on the reduced parameter space of important drivers, and, where appropriate, couple machine learning models with standard PDE models to capture important physical behavior at different scales. This work falls under Focal Area 2. Predictive modeling through the use of AI techniques.

Science Challenge

Arctic sea ice plays an important role in the Earth's climate by reflecting solar radiation, modulating heat and momentum flux between the atmosphere and ocean, and impacting ocean circulation by releasing freshwater during melt and brine during sea ice formation. Sea ice extent in the Arctic has been decreasing over the last forty years and previous generations of Earth System Models (ESMs) have generally underpredicted this loss [1]. Recent coupled model intercomparison results demonstrate that, for many coupled models, inconsistencies remain between surface air temperature and Arctic sea ice loss trends [2]. Moreover, sea ice components in many ESMs do not reproduce observational sea ice drift, particularly in summer months [3]. Accurate predictions of sea ice concentration, thickness, and velocity as well as long-term estimates of timing for a seasonally ice-free Arctic depend on a better understanding of the complex interactions between the ocean, atmosphere, and sea ice in the Earth system and of the limitations of ESMs in reproducing those feedbacks.

Rationale

Machine learning (ML) techniques can help elucidate differences in sea ice response between observational data and simulations to highlight important factors to guide improvements in sea ice prediction in coupled Earth system models. Research into modes of variability and the subset of atmosphere, ocean, and ice fields as well as climate modes that strongly influence predictability of sea ice are key to more skillful seasonal and long-term forecasts. Identifying the primary drivers of sea ice response can be difficult due to the complex interactions and feedbacks in the Earth system. ML techniques provide a method to investigate a smaller subset of important features to determine their role

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in generating skillful predictions as well as facilitate dimension reduction to develop effective surrogate models that enable efficient exploration of potential future trajectories.

Narrative

Arctic sea ice concentration and thickness evolve based on dynamic and thermodynamic responses to complex interactions with the ocean and atmosphere. The sea ice model in E3SM, MPAS-Seaice, incorporates sophisticated PDE-based models to capture physical processes and when forced with atmospheric data sets shows good agreement with observational data for sea ice extent and volume [4]. However, in E3SM the coupled interactions can lead to significant modeling challenges and sea ice response can differ from observations in both magnitude and overall trend. Ascertaining and mitigating the most substantial modelling errors is critical for reliable scientific understanding, communication, and preparation for future climate change and national security challenges. Machine learning may be able to provide metrics to pinpoint modelling or measurement errors, as well as bridge gaps between in modelled physics and real physical processes as described in the following sections.

Feature Analysis of Data-driven Arctic Sea Ice Models

Feature analysis provides insight into the most important drivers of sea ice in the coupled Earth system and difference in feature importance between simulation and observation trained data-models illuminates interactions to target for improved predictability. In previous work we investigated the most influential factors in predicting September average sea ice extent using machine learning models trained separately on observational data [5,6,7] and on simulation data from five E3SM historical ensemble members [8]. Monthly averaged atmospheric, oceanic, and sea ice variables for June, July, August, were used as input features to predict September sea ice extent in random forest regression (RFR) models, which were chosen to build the feature map because of their ability to learn nonlinear relationships between features and expose those relationships via Gini importance [9]. The RFR models successfully learned the data and demonstrated that six of the ten features were important in all simulations and observations, however, key differences in their relative importance merit further investigation [10,11]. There are significant opportunities for extensions of this preliminary work including adding more inputs or features to the data-model beyond Arctic-specific ocean, atmosphere, and sea ice quantities, increasing the temporal resolution of the input and output data, and extending the feature analysis to include training and prediction of sea ice extent over all months of the year. To enable investigation of regional differences in feature importance, extension of the analysis to data-models of gridded sea ice concentration and other important fields is key. The long-term goal of feature importance analysis comparing data-driven-models using simulation and observational training data is to advance understanding of Earth system interactions and provide a framework for physical model tuning and calibration that leverages observationally important drivers and feedbacks.

Machine Learning for Surrogate Modeling

The feature analysis provides insight into the most important inputs for simple ML models of sea ice in the coupled Earth system and can guide the process of developing more targeted spatio-temporal surrogate models. We propose developing ML surrogates for sea ice extent and concentration using recurrent neural networks or Autoregressive Moving Average (ARMA) models for time-series predictions. Recent ML approaches to determine causal connections between quantities can be applied to these time-series predictions [12], which will provide additional insight that builds on the correlative connections from the feature analysis. This insight will help guide the development of more accurate surrogates using a reduced parameter space, which can be used to efficiently evaluate sensitivity of sea ice response to parameter perturbations. The ultimate goal will be to explore the possibility of replacing components of the physical sea ice model with faster processes offered through ML surrogates. Extensive research will be needed to quantify and bound the uncertainties/error of the surrogate models. With knowledge of the uncertainties, researchers may be able to use these faster models directly, or at least use them to reduce the dimensionality of the simulated models. Generating sufficient simulation data to train the models is difficult given the computational expense of ESMs. To overcome this barrier, we will also investigate transfer learning approaches that can take advantage of training on low resolution data from simulations and then refine the training with higher resolution data [13].

Nonlocal Models to Capture Anomalous Sea Ice Dispersion

At high resolutions, PDE-based sea ice models using viscous-plastic rheologies cannot capture the observed sea ice dynamics. This has led to recent research in alternative rheologies as well as alternative non-continuum numerical discretizations, such as the discrete element method. Observational data on Lagrangian ice trajectories in the Arctic demonstrate that there are distinct regimes of spatio-temporal ice drift and there is evidence of anomalous diffusion that standard PDE representations cannot capture [14]. Nonlocal, fractional models may be able to capture this phenomenon by including multiscale and memory effects such as superdiffusion and subdiffusion thanks to their integral form that embeds different length- and time-scales. Furthermore, for some values of memory and dispersion parameters, these models are equivalent to classical PDE representations. Data-driven ML algorithms such as DeepONets [15] or nonlocal versions of PINNs [16,17] can estimate such parameters and identify the nature of the sea ice dynamics in certain regions or time periods. This results in an automatic coupling of anomalous and classical behavior, i.e. of nonlocal and PDE models enabling a scale-aware model of sea ice dynamics.

Summary

The research proposed here will increase the understanding of sea ice behavior in the coupled Earth system and improve the predictability of sea ice in E3SM through feature analysis and causal analysis of observation and simulation trained data-models, generating effective reduced-space surrogate models, and developing coupling methods for ML models with PDE-based models. The frameworks developed in this research would also have relevance for other Earth system components within E3SM.

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