Authors

Yawen Guan, Department of Statistics, University of Nebraska – Lincoln
Deborah Sulsky, Department of Mathematics and Statistics, University of New Mexico
J. Derek Tucker, Statistical Sciences, Sandia National Laboratories, Department of Statistics University of Illinois
Christian Sampson, University of North Carolina

Focal Area(s)

This proposal aims to develop and evaluate statistical models and machine learning algorithms for detecting and tracking features in spatiotemporal remotely sensed data with uncertainty quantification. We focus a particular application on the detection of sea ice leads and ridges in the Arctic and use these key sea ice features for model calibration and to gain insight into the physics of sea ice thermodynamics and deformation.

Science Challenge

A variety of remote sensing, in situ observations, and model simulation output are now available for geo-scientific modeling. In fact, we find ourselves in an era where data collection is far outpacing our ability to make meaningful use of it, providing unique opportunities and challenges for Earth System monitoring and modeling. Machine learning approaches have gained increased popularity and success in mining knowledge from data thanks to their capability for modeling complex nonlinear relations and the availability of convenient computational tools. While ML has been widely used in other areas, such as computer vision and smart transportation, it has only been applied to modeling a limited number of isolated Earth System features, including storm detection, teleconnection identification, and surrogate or sub-model parameterization of physical models to name a few. The limitations of ML approaches to Earth System modeling are mainly (1) black-box algorithms that limit interpretable prediction that is physically realizable, (2) difficulty in incorporating data uncertainty for model parameter estimation and in producing probabilistic forecasts, and (3) lack of a meaningful way to cope with multiple data sources and complex data structures. To expand ML approaches to general Earth System monitoring and modeling requires further development and adaptation to geo-scientific analysis.

Rationale

This whitepaper acknowledges a need to develop and evaluate statistical models, ML algorithms, and novel metrics for detecting and tracking important features in spatiotemporal data that are applicable in Earth System modeling. Further, there is a need for statistical model calibration, providing proper physics and uncertainty quantification, based on these features.

Traditionally, spatiotemporal statistical models explicitly capture the complex dependence in environmental processes that are often present across different spatial and temporal scales, but are limited due to computational cost as the data size grows. ML approaches, on the other hand, may not be optimal in the spatiotemporal context but might be better able to capture complex non-linear patterns in high-dimensional data. A comparison between, and sensitivity analysis for

DOI: https://doi.org/10.2172/1769711
DOE BER, AI4ESP 2021 #AI4ESP1054 (https://www.ai4esp.org)

these two approaches for feature extraction will provide insights on performance and potential for new methods that borrow strengths from both, building towards interpretable ML methods.

Bayesian hierarchical modeling has been widely used for model calibration. It is capable of fusing multiple data sources and physical models while accounting for uncertainties. However, Bayesian model calibration is often hindered due to the rising computational cost associated with increasing dimensionality and data complexity. A promising direction is to reduce data dimensionality by extracting low-dimensional key features and patterns from data and model output, then performing Bayesian calibration based on these key characteristics. Moreover, the traditional calibration approach often relies on metrics based on a pixel-wise difference. A vexing problem is the basic issue of how to compare predicted and observed features. A simulation with a slightly misplaced or misshapen feature would score worse than a simulation without the feature entirely using such a metric. For feature calibration, we have begun to explore metrics based on image warping to inform model parameters [Guan, et al. 2019].

Data Assimilation (DA) is a powerful tool for improving a model's predictive power, providing physical reanalysis, parameter estimation, and model evaluation. For any DA scheme relevant and informative data with a good measure of the data uncertainty is key. Data uncertainty plays a direct role in calculating how much model state variables should be adjusted based on the observations. When the data to be assimilated is of a highly localized coherent structure, a measure of the uncertainties in the location and geometries of those features provides for a more robust analysis of the model state. With data uncertainty such a critical part of any DA scheme, the development of methods to identify physical features which can provide uncertainty estimates is paramount. This implies some advantage to using statistical methods which provide uncertainty quantification (UQ) for feature extraction over techniques for which robust UQ is not possible. The statistical techniques proposed here have this advantage over some ML techniques which are less interperatable.

Whether performing state estimation or parameter estimation the choice of DA scheme for the model and physical system is also important. For example, many DA schemes work under a Gaussian assumption which is not always valid. Also, providing an accurate measure of the misfit between data and observation is paramount for successful DA. Variational DA methods can be thought of as generally applicable depending on how the variational problem itself is solved. Further they are widely employed in operational settings across a wide range of agencies that provide geophysical forecasting. Most variational DA schemes minimize a weighted sum of L^2 norms with the weights related to model and observational uncertainties. As explored in Guan, et al. 2019, the standard Euclidean metric is not always an optimal measure to compare simulations with observations. The exploration of new image-warping metrics tailored to a specific problem in a DA scheme is thus warranted.

Narrative

Arctic sea ice plays an important role in the global climate. Dominant features of the Arctic sea ice cover are leads and ridges. Leads are areas of open water caused by fracturing ice that occupy only 2% of the ice area in the winter but account for the majority of the heat transfer between the ocean and the atmosphere. Ridges are typically formed along leads as floes collide and force chunks of ice up onto the surface or below the surface into keels. Ridge and keel formation provides a mechanism to increase ice thickness per unit surface area. Analyzing these features provides valuable insights to the Earth's energy balance. Satellite synthetic aperture radar data have been analyzed via the RADARSAT Geophysical Processor System (RGPS) and indicate long linear features that can generally be associated with leads. However, there are some challenges that prevent the use of these features in monitoring and modeling the Arctic.

(1) RGPS images are available for patches of the Arctic surface at approximately a 3-day interval, at irregularly spaced points. The current approach approximates derivatives of these data to identify large deformation regions, even though fractures produce a discontinuous (non-differentiable) displacement field. Moreover, there is no uncertainty quantification associated with the detected features. A systematic and consistent detection approach that accounts for missing data and provides uncertainty quantification for the detected features is currently lacking. (2) A recent elastic-decohesive sea-ice model (Peterson and Sulsky 2012) has been proposed which explicitly represents the presence and direction of sea ice deformation features such as leads. It is necessary to calibrate the numerical model to the observed features for model evaluation and prediction. However, traditional calibration methods based on generalized least-square metrics are flawed for linear features such as leads.

We propose to address the above challenges by developing parametric and non-parametric spatiotemporal models for incomplete, discontinuous and motion data for classifying sea ice patches and extracting linear features from the patches. These results will be compared with Deep ML approaches such as convolution neural networks (supervised learning) where model outputs can be used as training data and hierarchical clustering (unsupervised learning) on observational data. Sensitivity analysis will be performed to see how different features are identified by the ML approaches when uncertainties and errors are present in data. The derived low-dimensional features and image warping metrics are then used for sea ice model calibration.

Beyond the initial focus on detecting leads in sea ice observations and using these detected features in model calibration, the proposed methods are promising for developing information about lead distribution and floe-size distribution for enhanced, high-resolution simulations of the polar regions. The feature-based calibration framework is also applicable to other applications where the focus is to understand the features generated by the underlying process. Code and documentation for carrying out feature detection and feature-based calibration will be made publicly available to facilitate dissemination of research to the broader scientific community.

References

Y. Guan, C. Sampson, J. D. Tucker, W. Chang, A. Mondal, M. Haran, and D. Sulsky, *Computer model calibration based on image warping metrics: an application for sea ice deformation*, Journal of Agricultural, Biological and Environmental Statistics, vol 41, pp 444–463, 2019

K. Peterson and D. Sulsky, *Towards a New Elastic-Decohesive Model of Arctic Sea Ice*, Physica D, doi:10.1016/j.physletb.2003.10.071 (2012)