BAMS
Meeting Summary

Advances in Machine Learning Techniques Can Assist Across a Variety of Stages in Sea Ice Applications

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International Sea Ice Modeling Workshop

What: A three-day workshop that facilitated networking and explored ways to integrate Korean expertise in machine learning with ongoing advances in sea ice modeling in the international community.

When: 24–26 October 2023

Where: Gwangmyeong, South Korea

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Forty-two researchers from South Korea, China, Australia, Canada, Belgium, France, Italy, and Norway were invited to discuss recent advances in sea ice modeling in order to situate future domestic research at the cutting edge of ongoing sea ice research in the international arena during a three-day (24–26 October 2023) workshop in Gwangmyeong, South Korea. Sea ice modeling is an emerging research topic in South Korea responding to 1) an operational need to understand sea ice variability at daily to seasonal time scales to support field campaigns and facilitate access to polar infrastructure and 2) a scientific need to understand sea ice variability at seasonal to longer time scales in terms of cryospheric change and future projections. Presentations from 21 invited speakers set the stage for four discussion sessions that were centered around four overriding themes:

1) emerging model technologies;
2) the role of artificial intelligence (AI) in sea ice applications;
3) model/observation integration;
4) future research needs and opportunities.

Workshop highlights

Discussion around new model technologies examined further improvements needed to the continuum model that is the base of most large-scale sea ice models, including numerical developments (e.g., a more precise advection scheme), new developments called for by new observations (especially rheology, but also possibly optics or thermodynamics), and new interfaces to other components of the Earth system model (e.g., wave–ice interactions and landfast ice). Better integration between DEMs and continuum models was emphasized as an important area of development, and ongoing research is examining the potential for blending these models for forecasting purposes.

There have been substantial advances in data collection over the last decade, especially sea ice thickness in the Arctic, where we now have almost year-round observations. A lack of observations remains an issue in the Southern Ocean, especially underneath the winter sea ice cover. Snow depth information has long been identified as lacking (e.g., Massom et al. 2001), and new satellite missions will hopefully provide a breakthrough in retrieving snow depth estimates (Tonboe et al. 2021). While satellite observations have significantly contributed to our understanding of sea ice deformation in polar regions, there is a need for enhanced and focused observations in the Southern Ocean (e.g., Newman et al. 2019). Improving the representation of atmosphere–ice–ocean interactions is the key to increasing the skill of sea ice forecasts. Prioritizing observations of the atmospheric boundary layer, surface-energy balance, and ocean mixed layer temperature and salinity, especially under sea ice, can support this effort. Making better use of existing platforms, such as drift buoys, Argo, and tagging of marine mammals, would help to collect these priority observations.

Two outcomes stood out from other commentaries on advances in sea ice modeling: 1) the explosion of AI techniques that may occupy a notable part of the field in the future and 2) the volume of sea ice related research in South Korea that is not yet well connected nationally or to the wider international sea ice community.

Application of AI techniques to sea ice research and forecasting. Only four years ago, at a sea ice modeling community meeting held in September 2019 in Laugarvtan, Iceland (Blockley et al. 2020), there was simply no mention of the use of AI in sea ice research. The development of machine learning (ML) techniques is progressing faster than previously supposed by our community, and these methods show potential as tools across the different stages of the sea ice forecasting workflow. AI approaches could be used for data pre- and postprocessing in support of traditional numerical simulations, to replace subgrid-scale parameterizations, and to directly produce sea ice forecasts. The employment of AI to a broad range of sea ice applications was showcased and discussed at the workshop. These applications include the following:

- Using various types of convolution neural networks (including UNETs) for forecasting sea ice concentration (Y. J. Kim et al. 2020), thickness (Durand et al. 2023), and extent probability (Andersson et al. 2021). ENSO forecasting with AI was also discussed to showcase the suitability of data-driven techniques for prediction tasks (Ham et al. 2019).
- Correcting biases in atmospheric boundary conditions for sea ice models using machine learning algorithms (Zampieri et al. 2023).
- Correcting sea ice model biases with ML parameterizations trained on data assimilation increments (Gregory et al. 2023a,b).
- Tuning poorly constrained rheology pattern descriptors using a deep neural network to identify the parameters that produce realistic deformation patterns (Korosov et al. 2024).
- Combining machine learning techniques (image segmentation, object correlation analysis, and machine learning) to detect landfast sea ice over West Antarctica (M. Kim et al. 2020).
- ML-based lead detection for better sea ice thickness retrieval from remote sensing (Lee et al. 2016, 2018) and, more generally, for enhancing observations.
- Emulators to predict the sea ice dynamics (Hoffman et al. 2023) or to replace subgrid thermodynamic parameterizations (Driscoll et al. 2023).

The pros and cons of integrating AI tools with more traditional physics-based sea ice models were discussed. A major advantage of machine learning techniques is that they are computationally much less expensive than physics-based models. One potential is to use AI to overcome bottlenecks in the physical models. For example, solving the momentum equation is computationally expensive and using an emulator for rheology could make this cheaper (Finn et al. 2023). Similarly, AI could speed up parameterizations by training on the model itself. The use of AI techniques for developing new subgrid parameterizations may also be beneficial, as it allows a more direct uptake of both in situ and remote sensing observations, reducing the empirical assumptions in our models and indicating a potential convergence between emerging neural network techniques and physical coupled models. Also, ML-based methods can provide a way to incorporate datasets into models. Finally, AI-based satellite emulators could bridge the gap between satellite-observed sea ice concentrations and the sea ice concentration defined in a model, an important difference that is rarely discussed.

However, it is important to note that while AI presents opportunities, there are also challenges and considerations to be addressed. The climate research community has already begun to assess the potential of AI for addressing climate change and its impacts (Cowls et al. 2021; Ham et al. 2023). Initiatives such as the NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography (AI2ES) are focusing on creating guidelines for the ethical and responsible use of AI in environmental science (McGovern et al. 2022). Haupt et al. (2021) highlighted the responsible and ethical use of AI in climate science to avoid misleading forecasters and users, the need for interpretability and trustworthiness of AI algorithms, and the incorporation of physical knowledge of the atmosphere in AI techniques as crucial considerations for the effective implementation of AI in weather and climate applications. We discussed limitations related to training the ML algorithms, including the fact that training is often on physics-based models and that training on observations inherits any defects in the products. These limitations suggest that although AI is going to assist, improve, and/or speed up many aspects of sea ice research workflows, it will not fully replace physics-based models. A final consideration is that although ML tools are extremely powerful and easy to use, these techniques have not been developed with sea ice applications in mind and must be adapted to our specific research questions. Fine-tuning these models is crucial; ensuring that the right (computer science) expertise is involved in future projects will be paramount to success.

Collaboration across geographies. A major aim of the workshop was to offer networking opportunities, especially to early career researchers in South Korea. We hoped to bring together Korean sea ice researchers, relate ongoing projects, and plan future work while drawing on expertise from the wider international sea ice community. One major achievement was to connect the variety of sea ice research taking place in institutes across South Korea, including observation programs in the Arctic and Antarctica, sea ice model development, and implementations of AI techniques. However, a surprising outcome was that the workshop highlighted the research bubbles that exist across geographies. International participants noted that they were introduced to relevant research in the field they had been previously unaware of, particularly the wealth of ML research taking place in South Korea. Future workshops will aim to strengthen the links between research in Asian institutes and universities and look for ways to highlight these programs to the international community.

Conclusions and next steps

The workshop provided a valuable forum for fostering collaboration and sharing technical knowledge, and the participants conveyed their appreciation for the opportunity to exchange ideas and build relationships. Future iterations of this workshop should not overlap with other ongoing initiatives but instead could provide a hub for researchers working in an Asian/Oceania time zone. A follow-up workshop is tentatively scheduled for fall 2025.

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