Sensitivity Analysis and Machine Learning of a Sea Ice Melt Pond Parametrisation

Simon Driscoll (University of Reading), Alberto Carrassi (University of Bologna/University of Reading), Laurent Bertino (NERSC), Julien Brajard (Sorbonne University/NERSC), Marc Bocquet (Écoles des Ponts ParisTech), Einar Olason (NERSC)

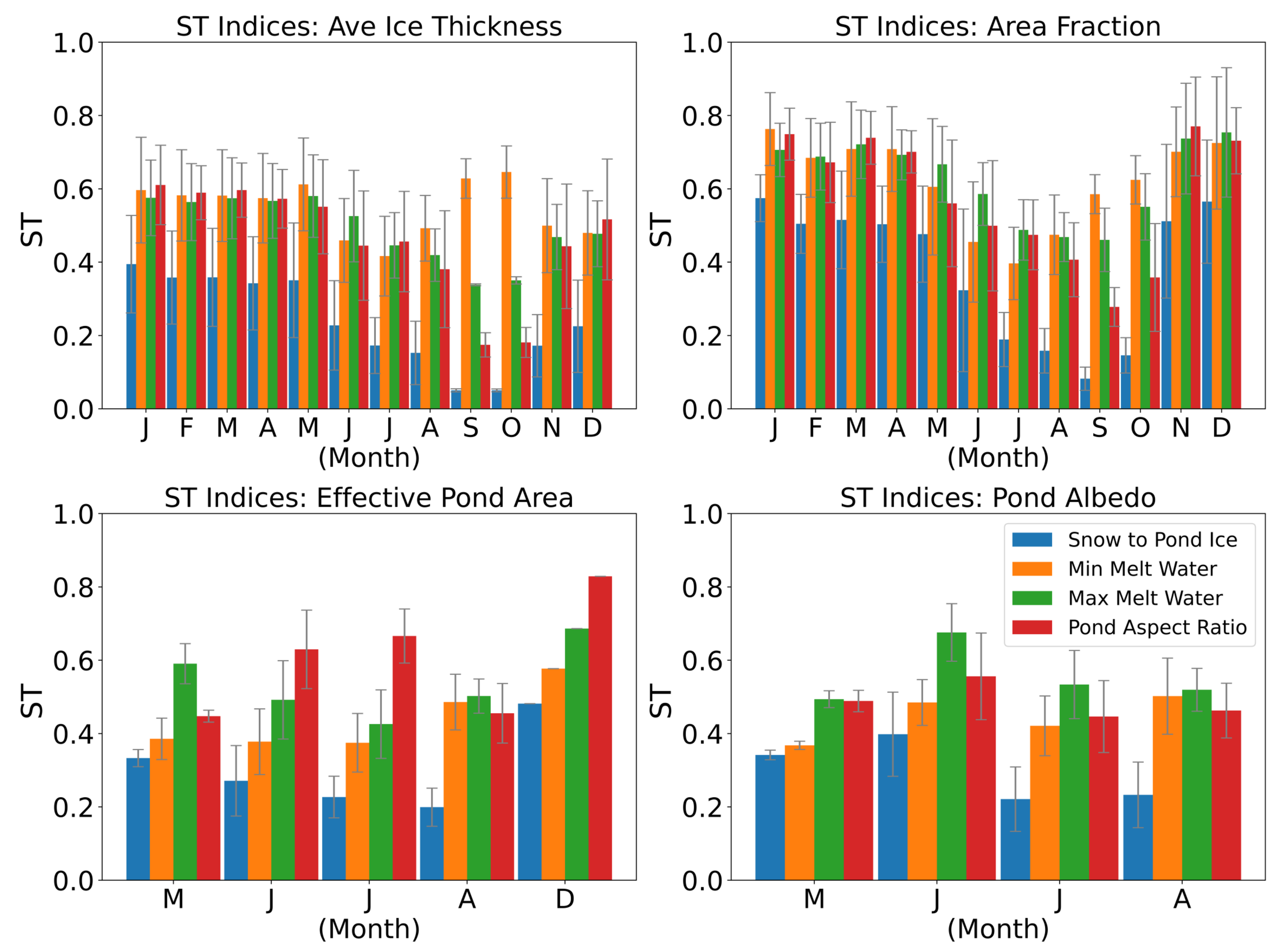
s.driscoll@pgr.reading.ac.uk

1) Introduction/Motivation

- Sea ice plays an essential role in global ocean circulation and in regulating Earth's climate and weather.
- Each year, during sea ice melt, ponds of melting water that cover up to 50% of the ice, and by absorbing more solar energy,, have a profound impact on the Arctic's climate.
- Melt ponds are complex, irregular, and sub-grid scale nature.
- Therefore they are parametrised in models. Their evolution being poorly understood, these parametrisations involve substantial **uncertainties**.

2) Parameter Sensitivity Analysis

- We use Sobol sensitivity analysis to assess the role these parameters play on the properties of sea ice in the state of the art Icepack column physics sea ice model (Hunke et al., 2013).



Total Order Sobol Sensitivity Indices for Area Fraction, Ice Thickness, Effective Pond Area and Total Albedo.

•Sobol sensitivity analysis shows that these uncertain parameters have contributions to key simulated sea ice variables that are sensitive not only to the season but also to geographic location.

•We propose substituting ``parametric parametrisation'', reliant on uncertain, internal and unmeasurable parameters, with a ``non-parametric parametrisation'' that can be calibrated using measurable quantities.

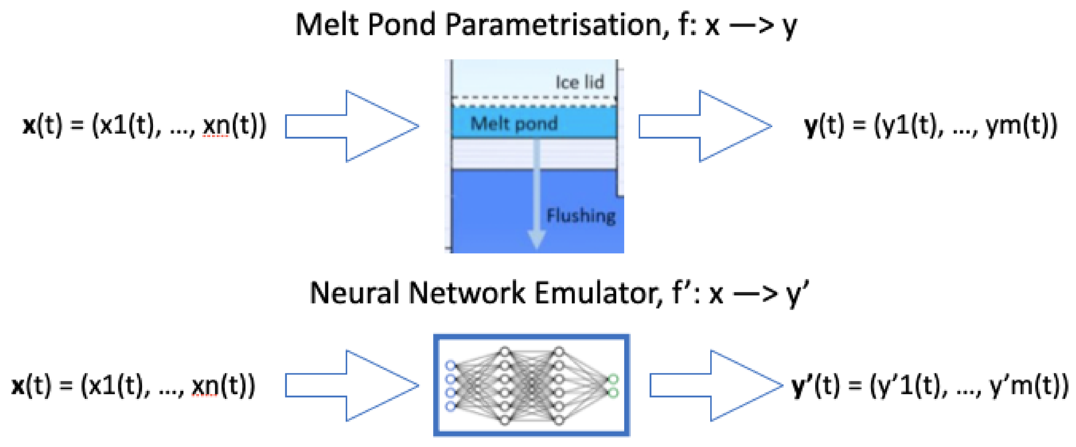
•To achieve this, we turn to neural networks.

3) Using neural networks to learn the melt pond parametrisation

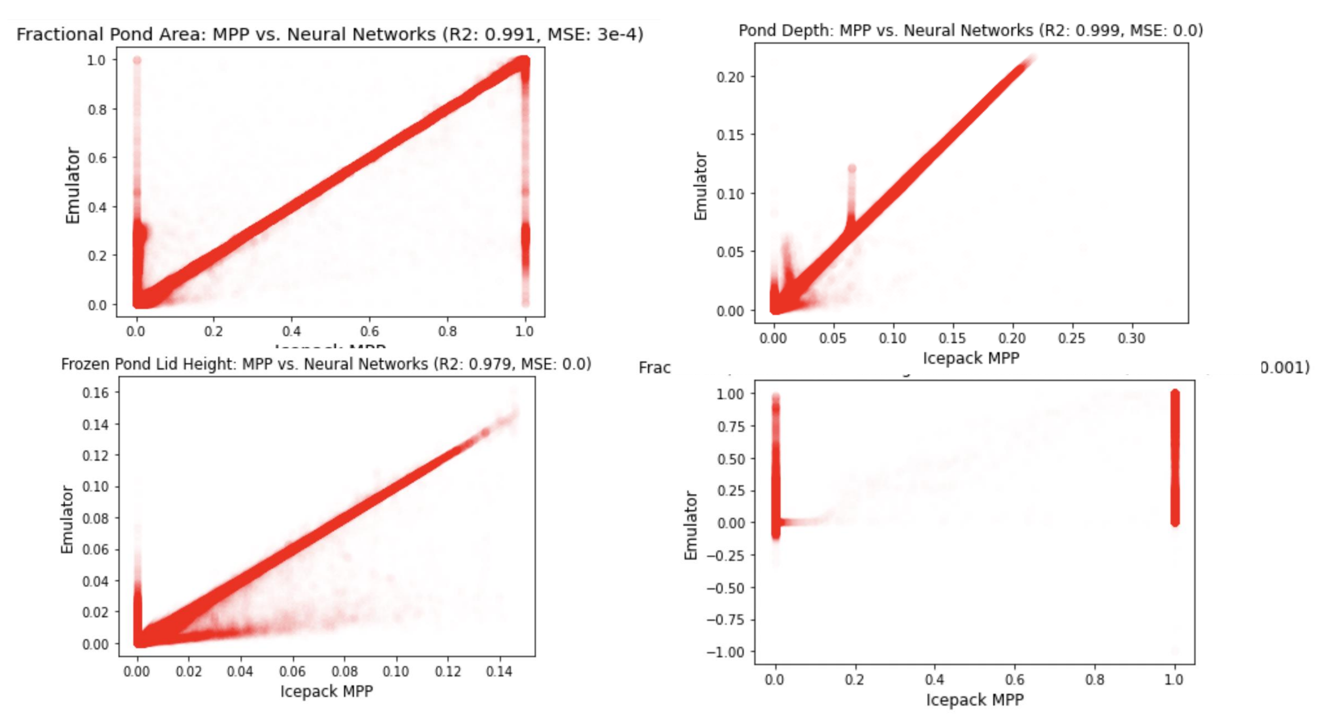
Given n features (independent variables), the melt pond parametrisation gives values for 4 targets: melt pond area, depth, thickness of lids on refrozen ponds, and fraction of heat flux used to melt refrozen melt ponds.

Melt Pond Parametrisation, f: x —> y

Neural Network Emulator, f': x —> y'



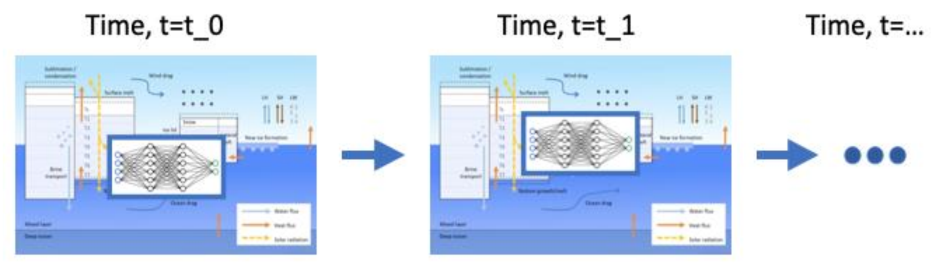
We initially train neural networks to learn this relationship. Scatter plots (below) show good MSE and R2 scores for neural networks prediction of the parametrisation's targets.



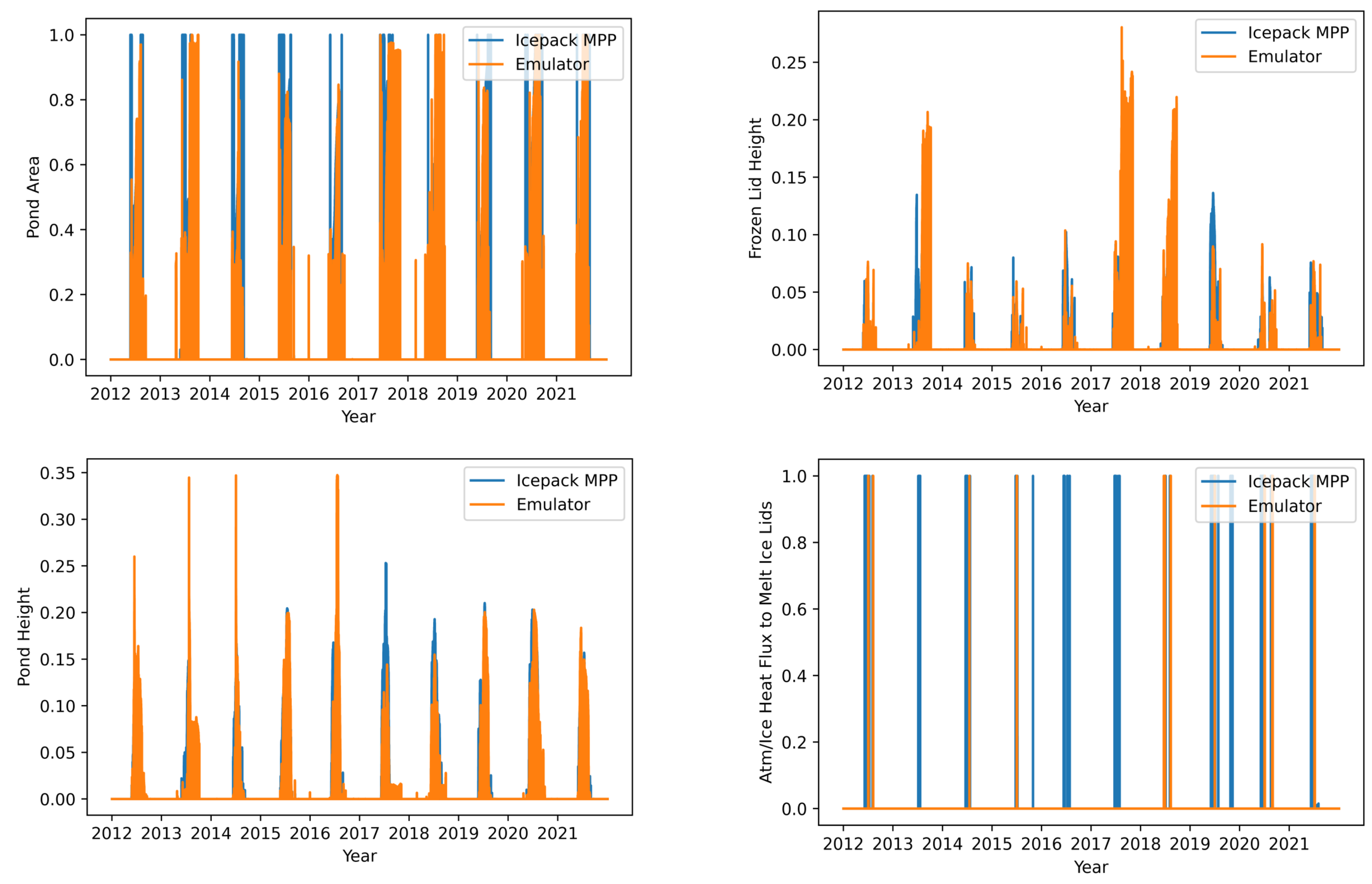
4) A neural network emulator of melt ponds

Once neural networks have learned to predict the melt pond parametrisation targets given its features, we replace the parametisation with the neural networks emulator, and run the Icepack model.

With Neural Network Emulator, f': x —> y', learned, we run ``IcepackML''.

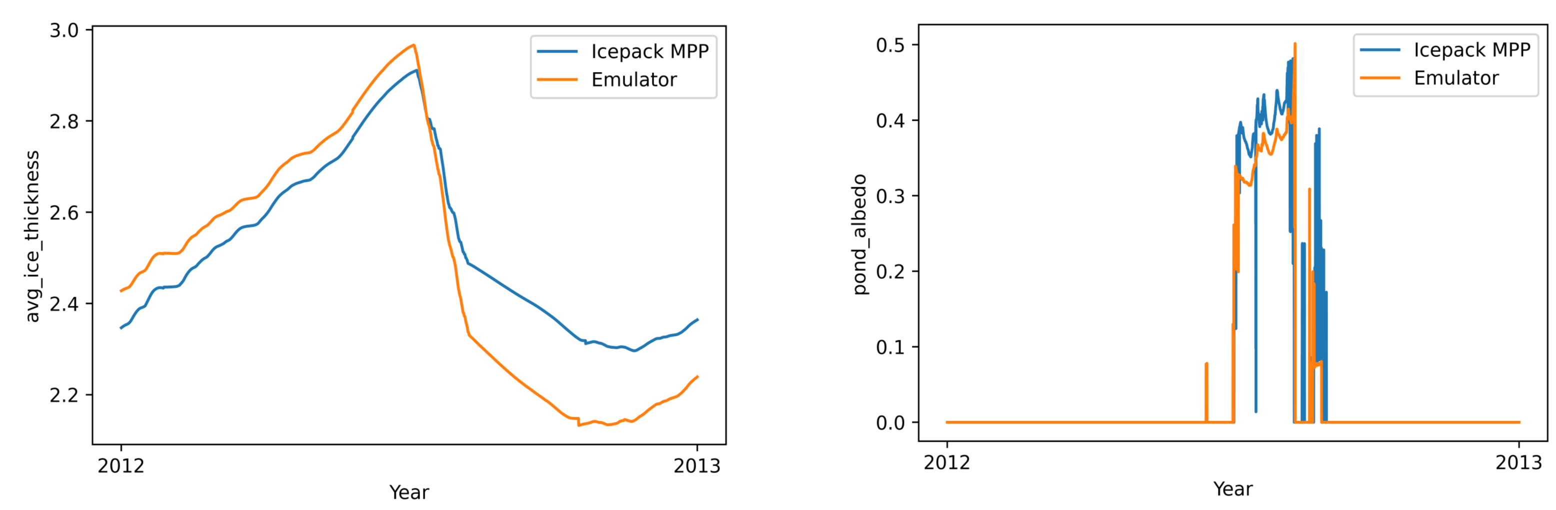


We can learn and emulate the relationship in the melt pond parametrisation, where the emulator can replace the melt pond parametrisation in the model so that Icepack runs successfully (below).



5) Prediction of key sea ice variables when using the emulator vs. melt pond parametrisation in Icepack

Simulations of the Icepack model with the melt pond parametrisation or with the emulator of this parametrisation show similar values, an absence of drift or instability, and that altering the representation of melt ponds can have substantial influence on key predicted sea ice properties. (below: average ice thickness (left) and pond albedo (right))



6) Conclusions and Future Work

- Our emulator can learn and replace melt pond parametrisations, and run in the Icepack model, without drift or instability.
- We seek to create an observationally trained/data driven emulator of melt ponds.
- The aim of our work is to produce an observationally trained emulator, capable of representing the complex thermodynamic physical processes that govern the evolution of melt ponds, and in turn capture processes crucial for e.g. predicting future sea ice loss.

This project is supported by Schmidt Futures – a philanthropic initiative that seeks to improve societal outcomes through the development of emerging science and technologies.