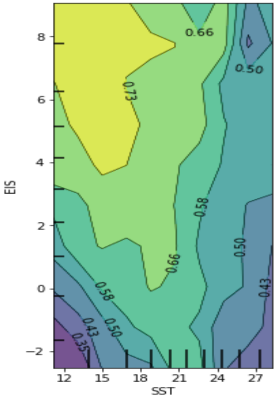
Predicting pre-industrial warm cloudiness using ML

Compare a multivariate linear regression (MVLR) with stochastic gradient boosting (SGB) and random forest (RF) ML models in order to predict a pristine cloud fraction as pre-industrial proxy and a comparison against the actual, observed cloud fraction

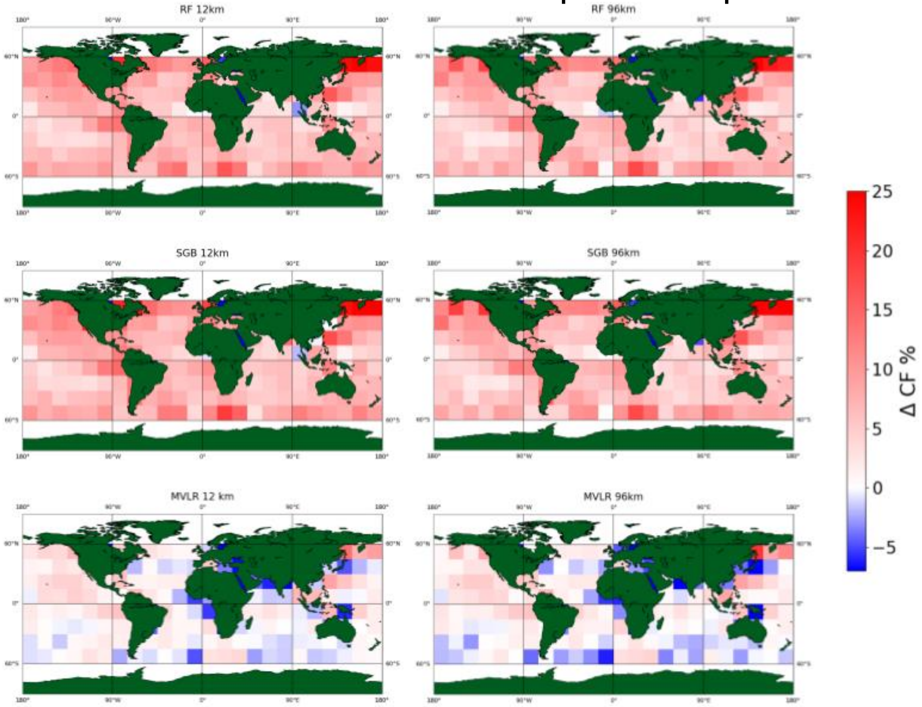
Aerosol-cloud interactions may have increased global cloudiness by 1.15% leading to a cooling effect of -.31 Wm²

The RF and SGB have less than 1% error in predicting pristine cloudiness, while the MVLR has >7% error

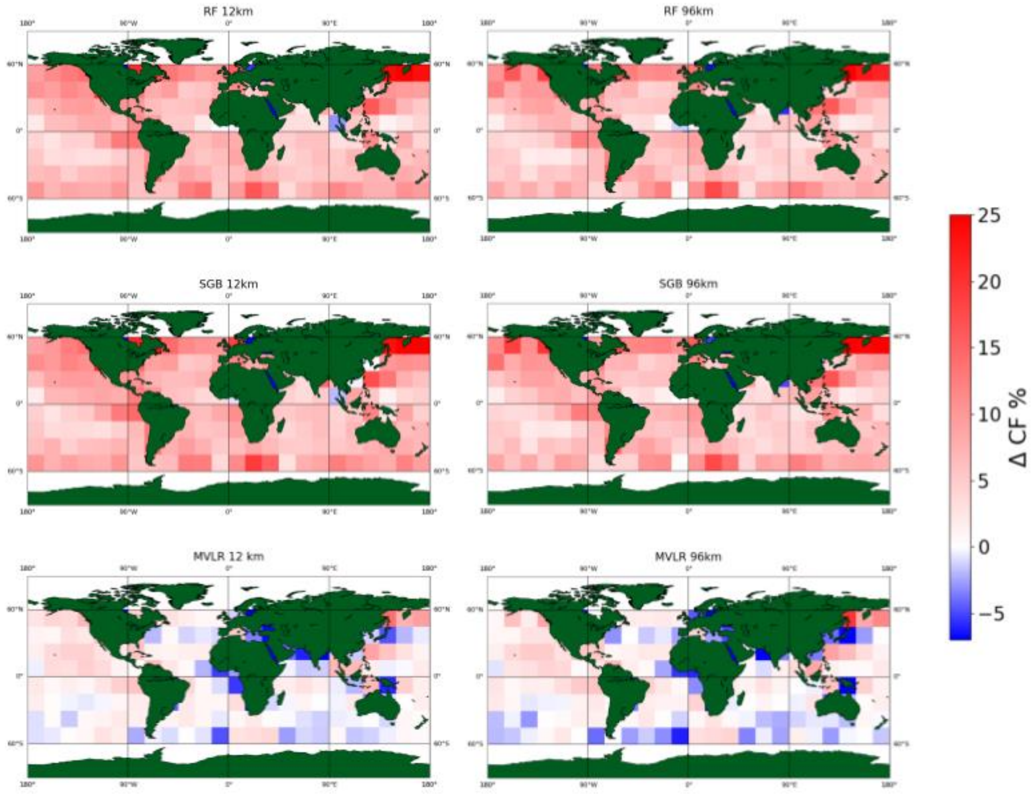


The learnings of the ML models can be used to understand ACI and the errors in current parameterizations of ACI in GCMs

$$\Delta\ \mathbf{CF} = \mathbf{CF}_{\text{actual}} - \mathbf{CF}_{\text{predicted pristine}}$$



RF, SGB suggest the north Pacific storm track region in particular has shown large increases in



Studies based off sensitivities alone may miss this signal as it may not be strictly linear

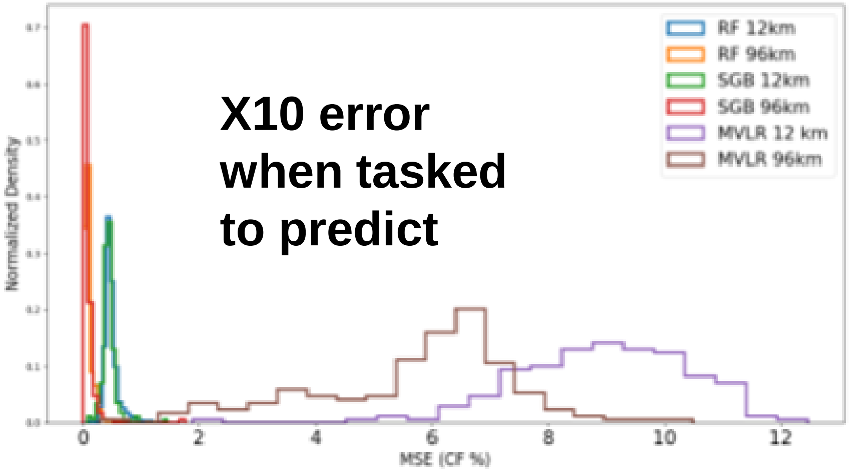
Environment-cloud interactions may overrule aerosol-cloud interactions, which obscures the signals when only finding a sensitivity

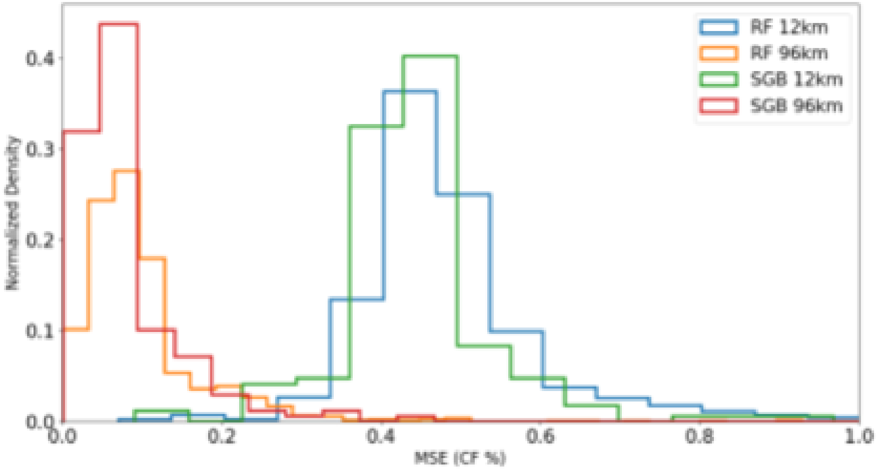
MVLR does not show coherent regional patterns or the same magnitude of changes as the SGB and RF

MVLR more prone to error, suggests may not be suitable for understanding more complex interactions in the Earth system

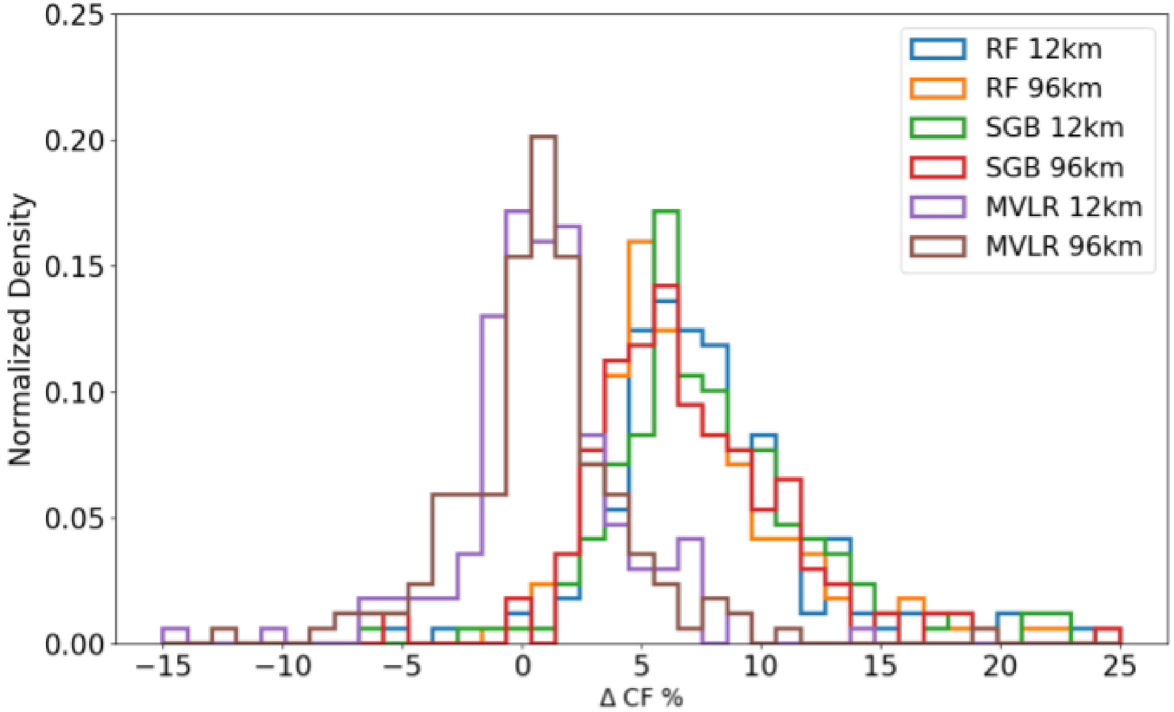
SGB, RF error is less than 1% cloud fraction

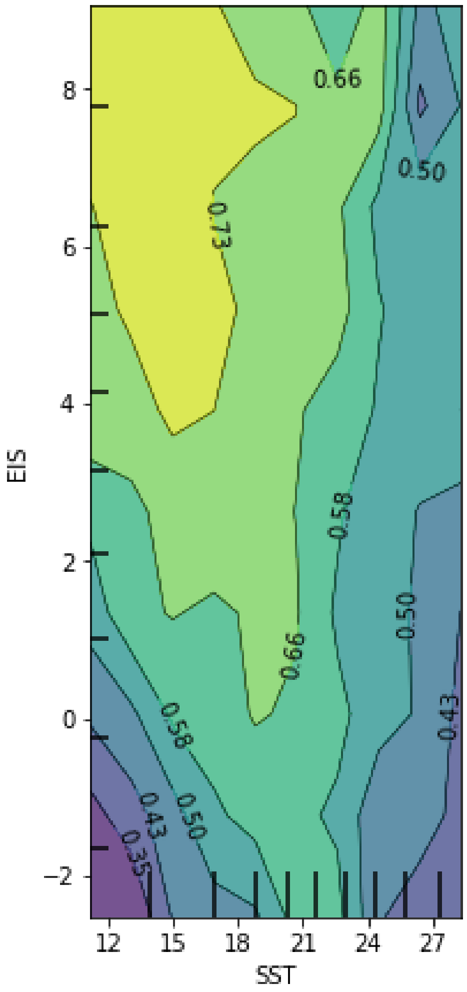
Frameworks can represent non-linear interactions





An MVLR based estimate would show almost no change in cloudiness from pre-industrial times most clouds, contradicting prior knowledge on warm clouds





The learnings of the models can be used to inform our understanding of the processes involved in cloudiness and other cloud processes

These can be used as comparison against GCM parameterizations to help inform what regimes have inaccurate representations

The latent space representations in more complex types of ML such as neural networks could be used to similarly distill the complex relationships into explainable figures