Evaluating the Efficiency of Autoencoders for Dimension Reduction of Sea Ice Data

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Antarctic sea ice modeling has become essential due to the exacerbating effects of climate change on the region, with the aim of utilizing present and past data to predict the future. However, a setback lies in the grand scale of the data needed to make these predictions best, spanning both spatial and temporal axes. As a result, dimension reduction is necessary to capture the most important patterns of variability – a pre-processing step for future predictions. The utilization of Machine Learning tools, such as autoencoders, has been investigated as an alternative to linear dimension reduction methods, such as EOFs. Input data includes satellite-observed gridded data in the Antarctic region from 1979 to 2022. Different versions of the autoencoder model are investigated, with varying components in its architecture, including activation function (linear and ReLU), bottleneck units (compressed dimensions), and added layers. It is found that the seven-layered and five-layered ReLU models outperform other configurations across all bottleneck units, including when compared with EOFs. These models also contain a higher explained variance ratio: at 11 compressed dimensions, the seven-layered autoencoder can capture 18.7% more variance than the 11 EOF modes explain. The ReLU activation function also allows the model to detect nonlinear patterns, providing an additional benefit to the improved RMSE and variance ratio. The findings demonstrate that the autoencoder model serves as a worthy alternative to EOFs, likely extracting more predictable variance in the sea ice field. The result is crucial for understanding sea ice spatiotemporal variability and its predictability in the Antarctic.