Generating Antarctic Sub-shelf Melt Using Recurrent Neural Network-based Generative Adversarial Networks on Spatiotemporal Pixel Clusters

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Ice loss from the Antarctic Ice Sheet is a dominant contributor to global sea level rise due to the recent warming of the ocean. However, many critical factors are poorly understood: how much of this melting is (1) anthropogenically driven, (2) caused by internal climate variability, and (3) how it affects uncertainty in projections of future sea level rise. In order to address these unknowns, we must generate many realizations of spatiotemporal ocean melt variability, which are extremely limited and expensive to produce with climate models. Thus, this work presents a new end-to-end machine learning approach to efficiently generate additional realizations of the stationary component of variable ice shelf melt. We use output from a state-of-the-art model of the Earth System (E3SM): a single 150-year simulation of pre-industrial global climate, with high-resolution melt rates calculated underneath floating Antarctic ice shelves. First, we do hierarchical agglomerative clustering with a custom spatial-temporal distance function in order to identify stationary subspaces with both independent spatial extent and independent internal variability. We then generate data from these stationary regions individually using a Generative Adversarial Network (GAN) capable of preserving temporal dependencies via recurrent neural network-based generative modeling. GANs gained popularity in generating photorealistic imagery, but recently spread to other, non-raster data types like time series. Contrary to explicit statistical models that assume a functional form of the underlying data distribution, GANs learn an implicit representation: a 'generator component' tries to fool a 'discriminator component' to accept artificially generated examples as true data points, while the discriminator learns to distinguish between artificial/'real' examples (the components are built on arbitrary artificial neural networks). We provide initial results indicating our approach can identify stationary clusters that make physical sense, and from which we can generate further realizations containing the complex statistical properties and stationarity in the original simulated data. Future work will include probabilistic machine learning approaches to quantify uncertainty in projected sea-level rise and model validity.

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