CryoStrat-RL: A Dynamic Graph-Game Framework for Arctic Conservation Using Reinforcement Learning

Chopra, Ryka (School: Mission San Jose High School)

Arctic sea ice and permafrost are critical to global climate balance and bio-geophysical diversity. Recent CryoSat-2 satellite data indicates that ice thickness is depleting at the rate of 12.5% per decade, contributing an additional 29% over the baseline global temperature increase of 1? since 1880. In this backdrop, conserving Arctic ice is essential for global climate stability. Ice depletion results from both natural and anthropogenic stressors. However, current generation 1 physics-based models and generation 2 deep learning approaches lack a comprehensive framework to capture the interconnectedness between the two, focusing primarily on short-term ice melt forecasting. This reduces our ability to identify effective conservation policies, which are derived from long-term forecasting. In this research, I propose a dynamic graph-game framework to provide a unified model for Arctic ice prediction and conservation research. The framework employs a double-graph structure combined with game-theoretic strategy updates to establish a circular feedback loop between ice evolution and human strategic behavior over iterative time periods. Reinforcement learning–based strategy updates integrate both immediate impacts and long-run outcomes, allowing the model to adapt continuously. When embedded within an IceNet-inspired deep learning architecture, the model improves long-term predictive accuracy by 25.1% over IceNet forecasts. Additionally, when stakeholders adopt forward-looking learning rules like reinforcement learning to optimize strategy, voluntary cooperation emerges as a dominant Nash strategy. This cooperative outcome reduces the Arctic ice melt rate per decade from 12.5% to 4.1%, achieving significant conservation without resorting to expensive alternatives.

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