



Mapping sea ice coverage around Antarctica by using microseism and machine learning

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The most continuous and ubiquitous seismic signal on Earth is the microseism, closely related to ocean wave energy coupling with the solid Earth. A peculiar feature of microseism recorded in Antarctica is the link with the sea ice, making the temporal pattern of microseism amplitudes different with respect to the microseism recorded in low-middle latitude regions. Indeed, during austral winters, in Antarctica the oceanic waves cannot efficiently excite seismic energy because of the sea ice coverage in the Southern Ocean. Hence, there is a close relationship between sea ice coverage and microseism. An analytical approach to spatially and temporally reconstruct the sea ice distribution around Antarctica on the basis of the microseism amplitudes, based on microseism wave propagation, seems to be impracticable for the few and sparse data available in a highly heterogeneous and complex environment that would conduct to a strongly underdetermined ill-posed inversion problem. For this reason, we exploited the capabilities of the newest regression algorithms in machine learning to reconstruct the sea ice field starting from the knowledge of the microseism features or their transformations. In particular, the method we used is composed of three main steps: i) data preparation; ii) training; iii) cross-validation. As for the step (i), to exploit the maximum information content of the microseism data, we applied the following transformations on all the RMS amplitude time series: probability integral transformation, Linear Discriminant Analysis, Time Smoothing. Concerning the training step (ii), we exploited the potentiality of machine learning techniques (MLTs) to build a regression model able to predict the sea ice coverage from microseism-related features. In particular, we tested the following supervised machine learning techniques: Linear Regression, Random Forest Regression, K-Neighbors regression, and Extremely Randomized Trees Regression. Finally, regarding the last step (iii), we evaluated the unbiased generalization capacity of each pair MLT/input features by calculating the prediction performance through K-fold cross-validation.