inverting seismic properties of subsea permafrost zones using deep learning: lessons learned from four different domains.

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 Monitoring the state of permafrost is of primer importance for forecasting global warming. Subsea permafrost, which can include intra-permafrost gas hydrates, acts as a methane reservoir. However, with the increased temperatures associated with global warming, permafrost degradation is accelerated, leading to the emission of additional greenhouse gases through a feedback effect. Since seismic wave velocities correlate to the ice content in the pore space of sediments, seismic methods can detect ice-bearing or ice-bonded subsea permafrost and be used to map and monitor permafrost conditions. However, although seismic methods can accurately map the lateral distribution of permafrost, they often fail to resolve its vertical distribution. On one side, no critical refraction occurs from the velocity inversion at the base of the permafrost. On the other side, the high impedance contrast between the air, the water column, and the frozen sediments acts as a leaky waveguide that traps seismic waves in the water column. As a result, high amplitude guided waves and multiples travelling in the waveguide hide early reflections with weaker amplitude, including the reflection coming from the base of the permafrost. This severe interference between wave arrivals hinders their separation before implementing a classical pre-stack or post-stack inversion scheme. In this work, a deep learning approach is implemented for inverting seismic properties of subsea permafrost. Common seismic processing techniques convert the recorded seismic data in the time offset (t-x) domain into other domains to separate different events like primaries, multiples and guides waves. We test whether using different data transformations helps a neural network take advantage of the different wave types seen in the presence of subsea permafrost. We build four similar NN that have inputs in a different domain: time-offset (t-x), Radon (𝜏 -p), frequency-phase velocity (f-c) or frequency-Radon (f-p)). Each NN returns the P- and S-wave velocities and the inverse quality factor (1/Q). We trained the four NNs using 36000 synthetic samples built using simplified tabular models, representative of permafrost conditions found Canadian Beaufort Sea. We evaluated the performance of the NNs on synthetic 1D models and calculated the L1 and L2 norm of the errors. The NN with inputs in the 𝜏-p domain provides the lowest L1 norm error for Vp and 1/Q, while the lowest L1 norm error for inverting Vs is found in the NN with inputs in the (t-x) domain. Similarly, the 𝜏-p NN provides the lower L2 norm for Vp, Vs and 1/Q. Furthermore, we evaluated the NNs on synthetic data built on a 2D permafrost wedge model. Here, the L2 norm of the Vp errors was lower using a NN with f-p inputs. The lower Vs L2 error was obtained using a NN trained with f-p inputs, and the lower 1/Q L2 error using the NN trained in the t-x domain. Although the resulting models differ, the inversion accuracy is relatively high, with errors lower than 10% for the 1D models and 18% for the 2D models. We found that NNs trained with different input domains will accentuate distinct permafrost features during the training. Therefore, a combined analysis of the individual outputs can further improve the accuracy of the output model. In fact, after taking a simple average of the 2D models obtained, the wedge-shaped structure is better recovered. Finally, we evaluated our NNs using seismic data recorded on the continental shelf of the Beaufort Sea. We found that the average results from the NNs agree with previous studies of permafrost distribution in the study area. Finally, our results suggest that the deep-learning approach is suitable for mapping subsea permafrost distribution on a large scale in cost-effective manner.