

Experimental Design for Bathymetry Editing

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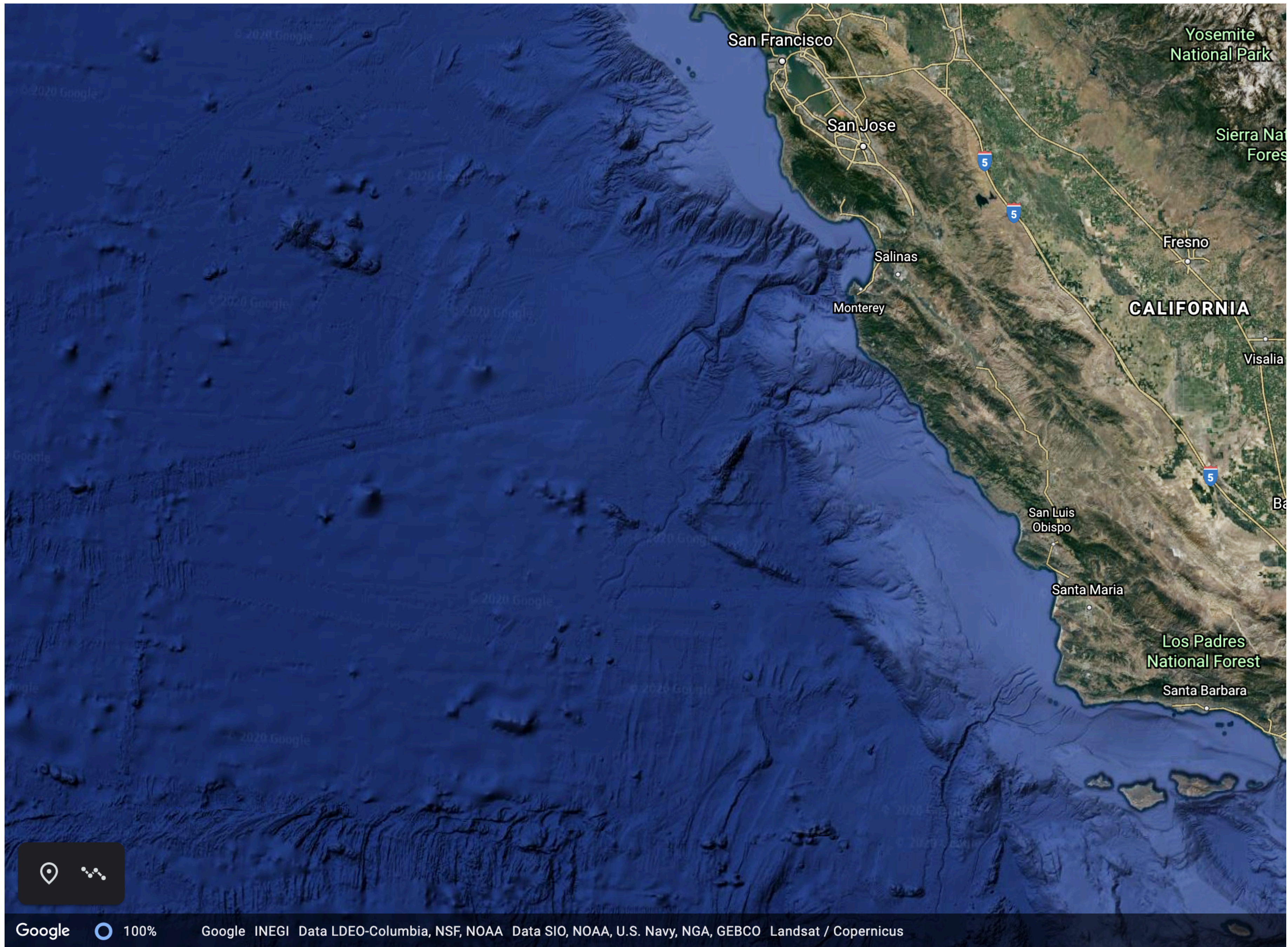
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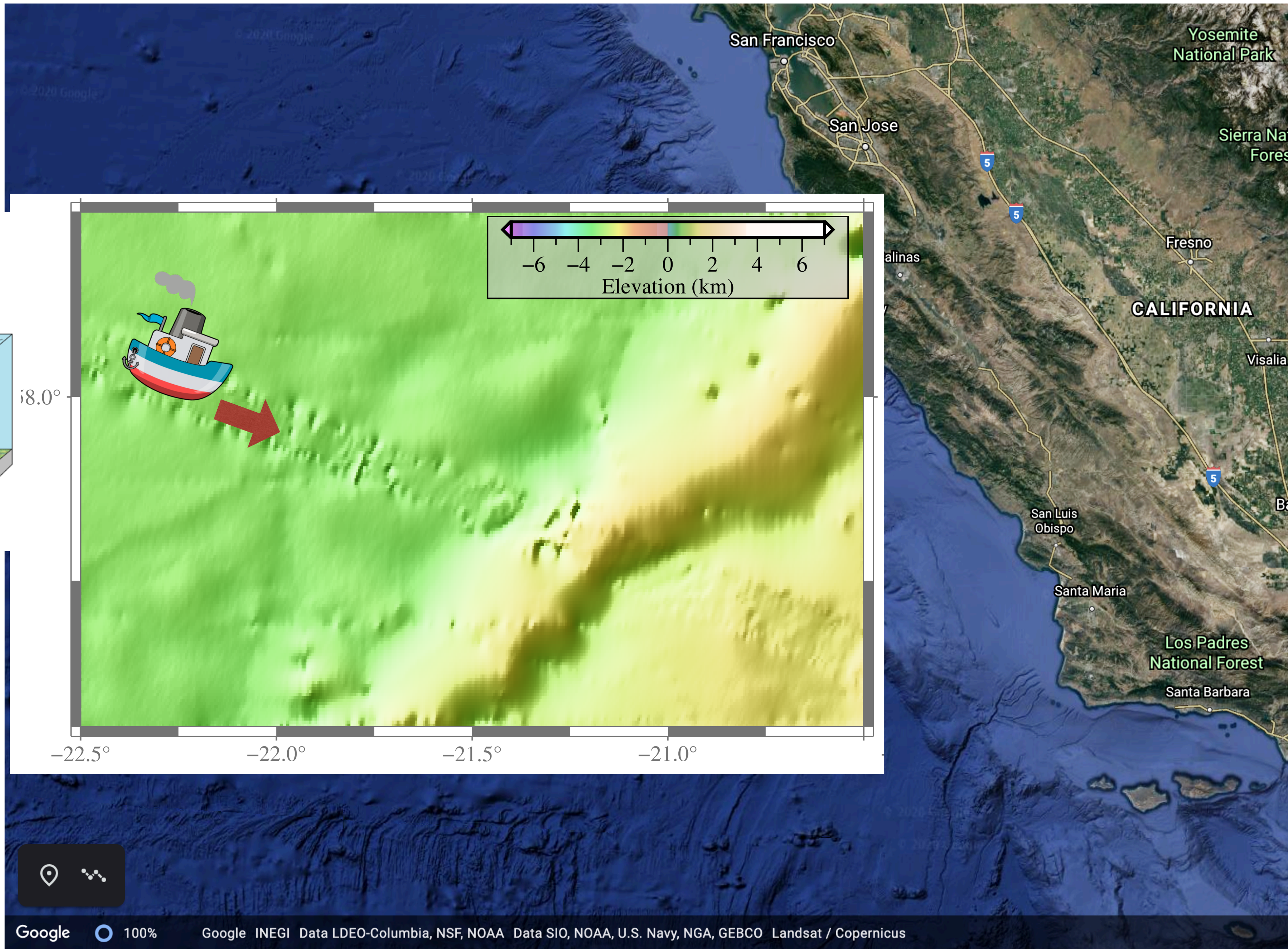
Workshop on Real World Experiment Design and Active Learning at ICML 2020
July 18, 2020



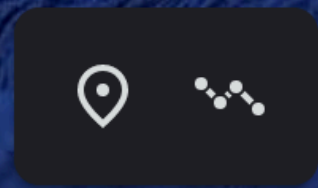
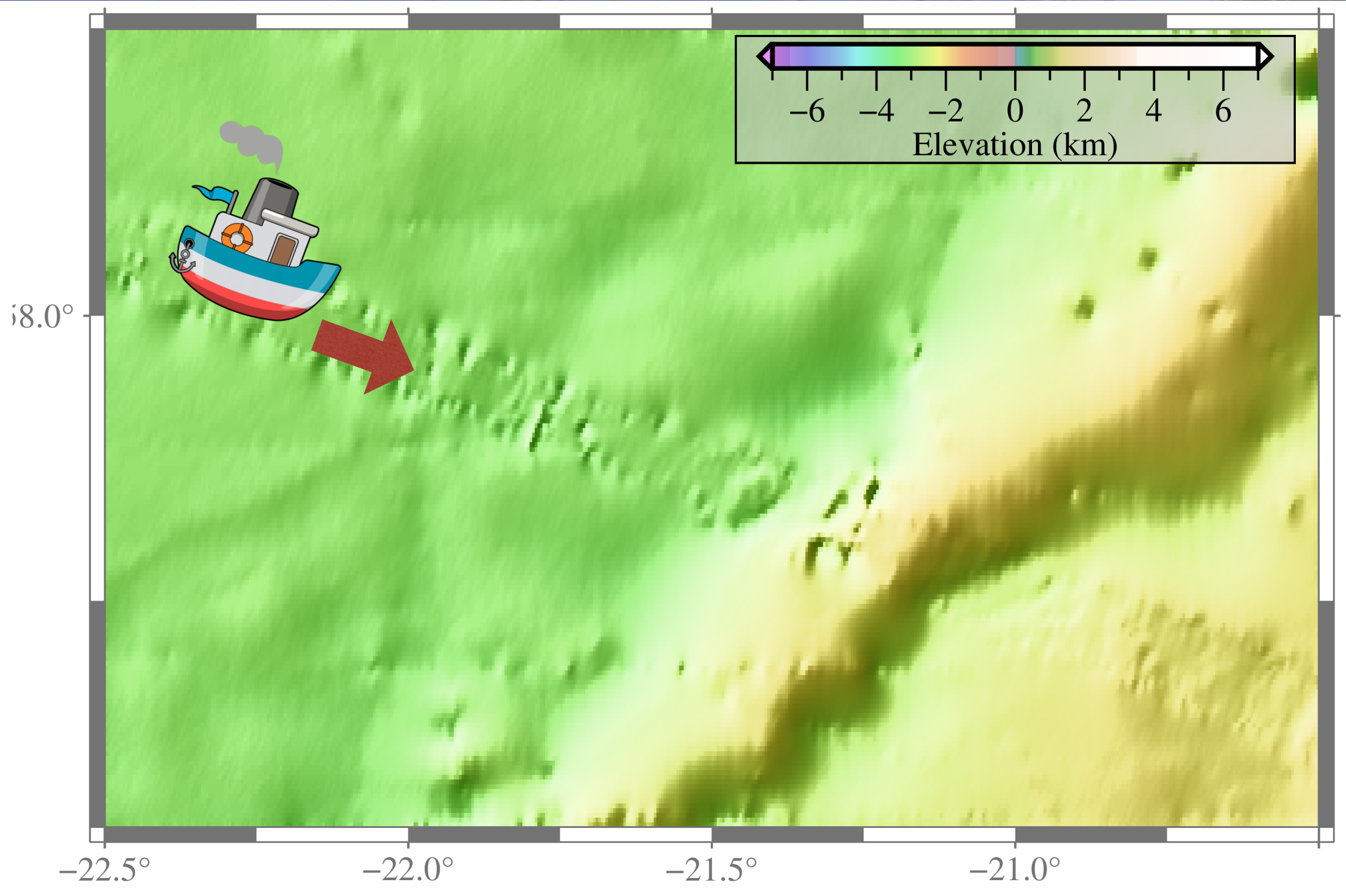
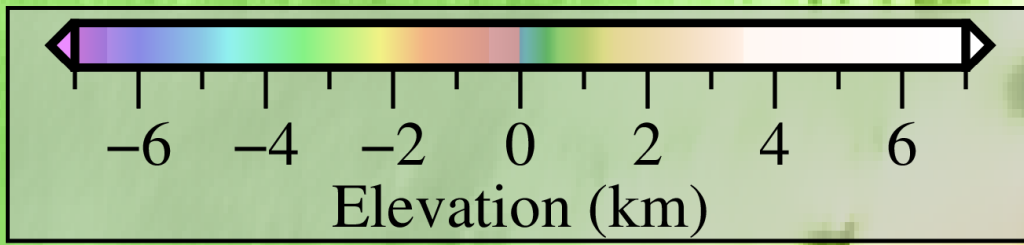
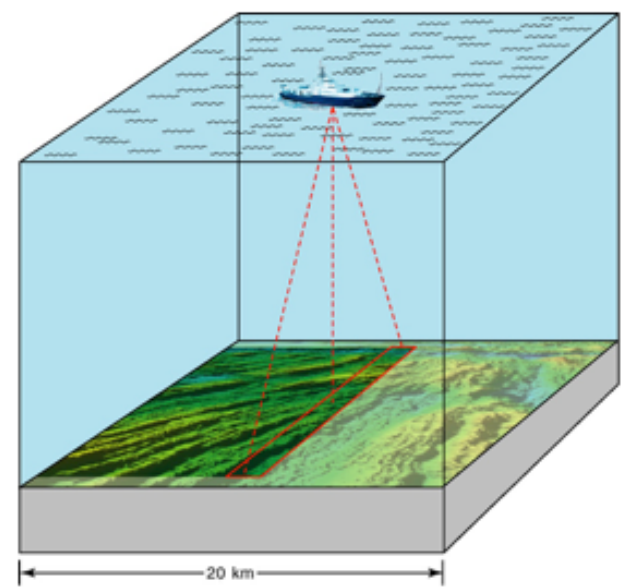
Google

100%

Google INEGI Data LDEO-Columbia, NSF, NOAA Data SIO, NOAA, U.S. Navy, NGA, GEBCO Landsat / Copernicus



**shipboard
echo sounder**
(high resolution ~100 m,
poor coverage 11%)

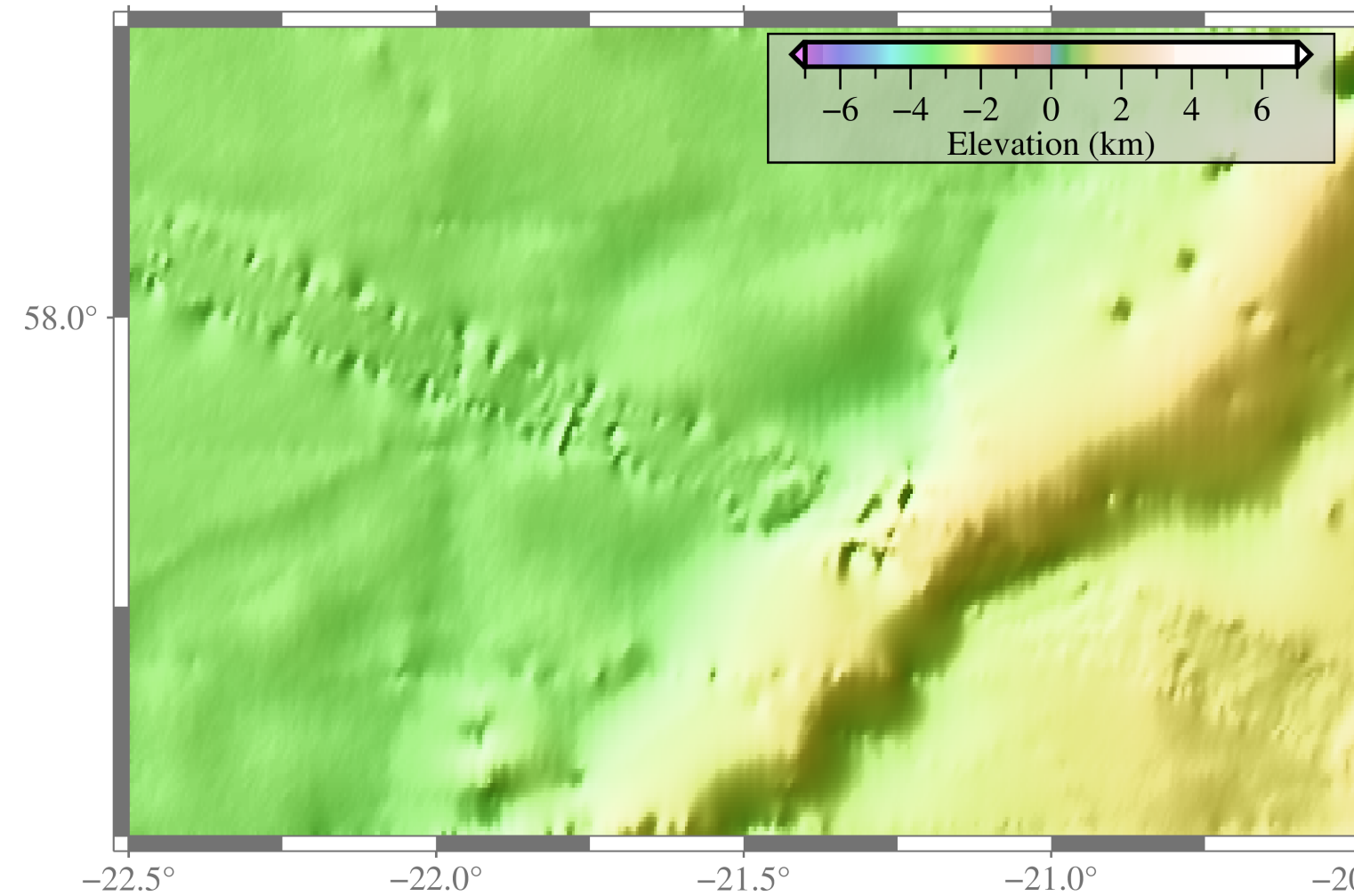


Computer-aided bathymetry data editing

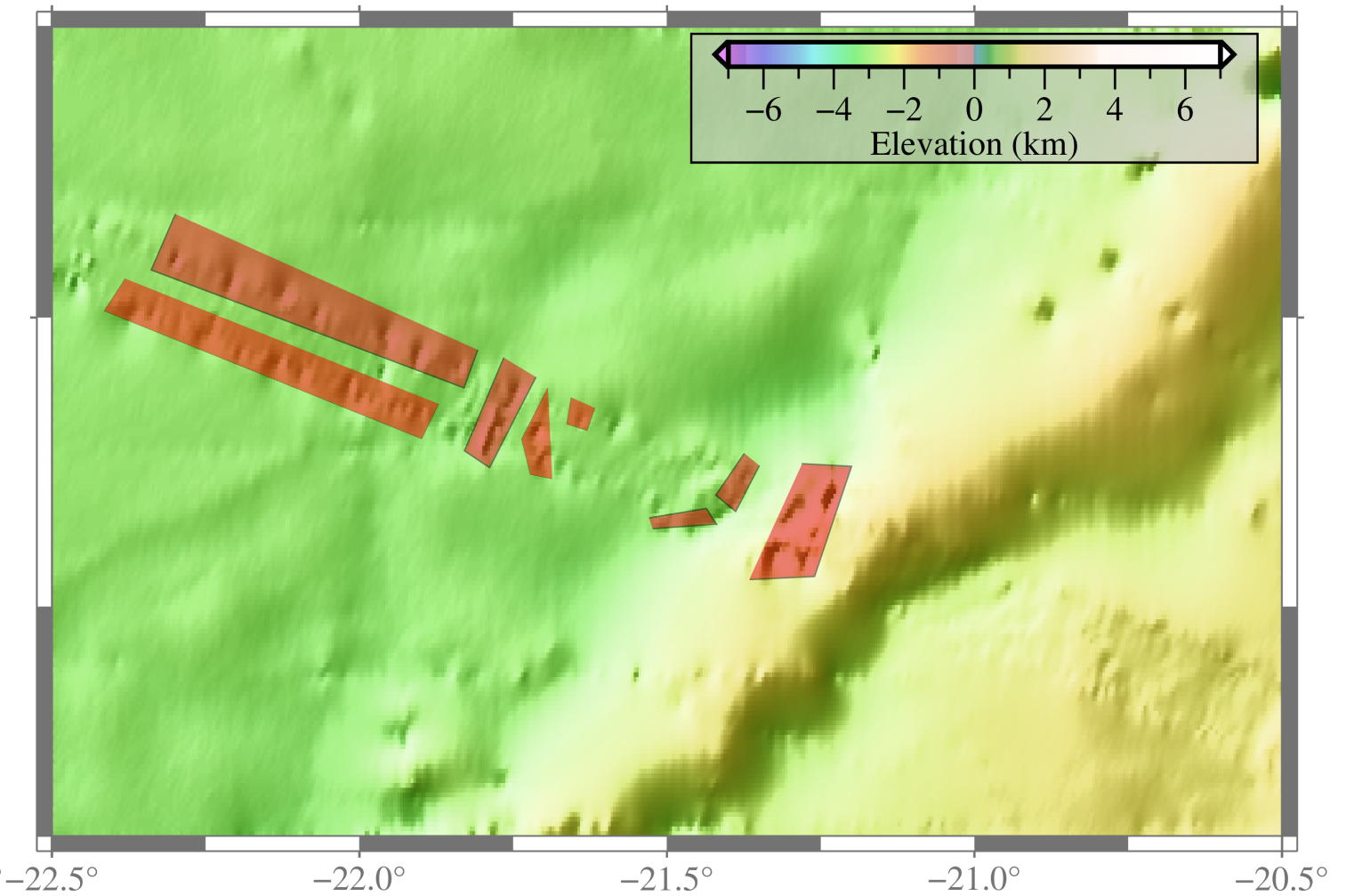


Manual editing

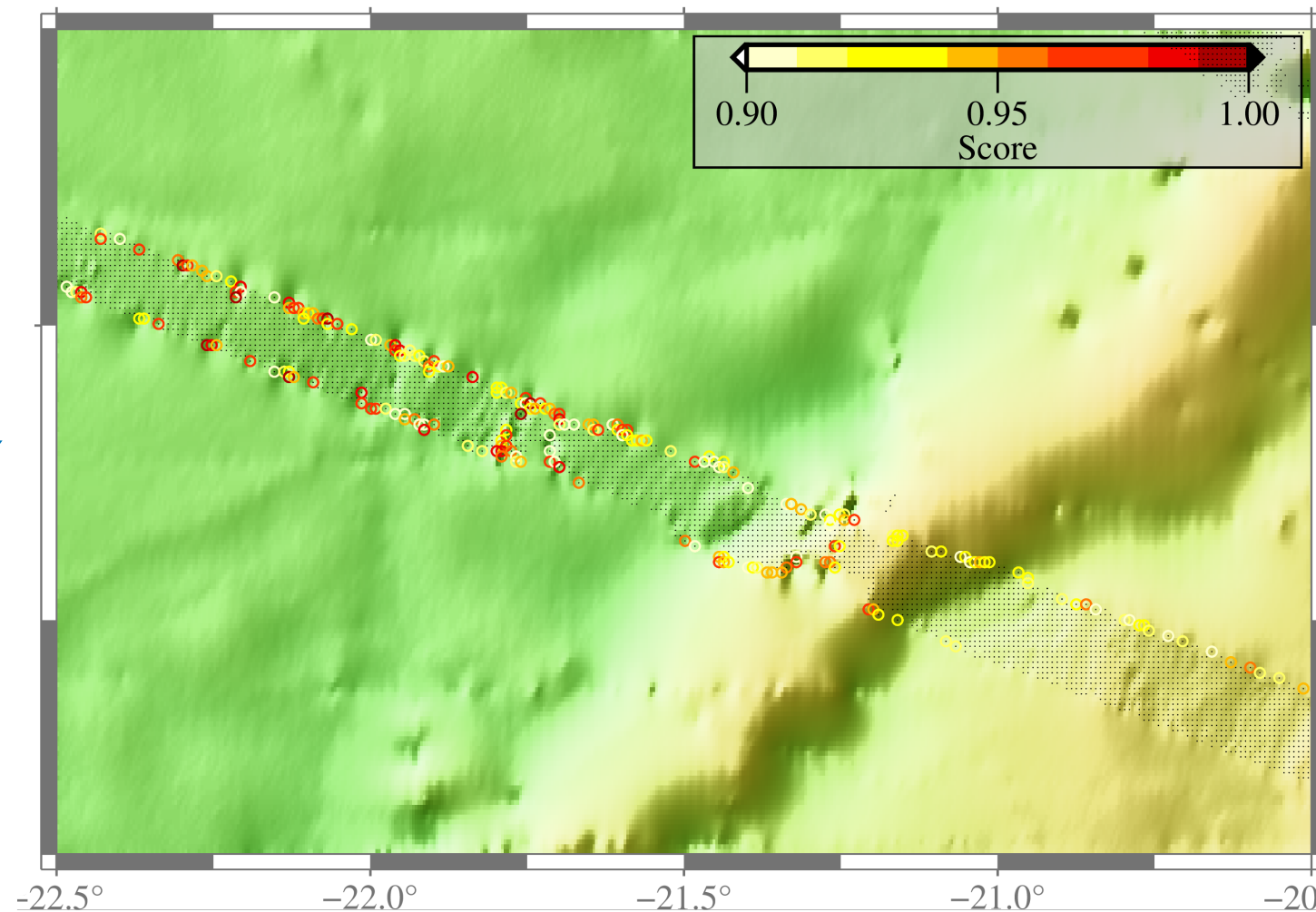
(a) Bathymetry depth measures



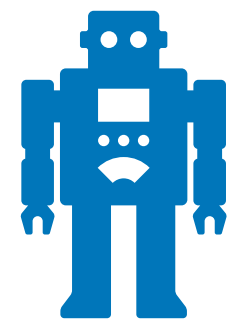
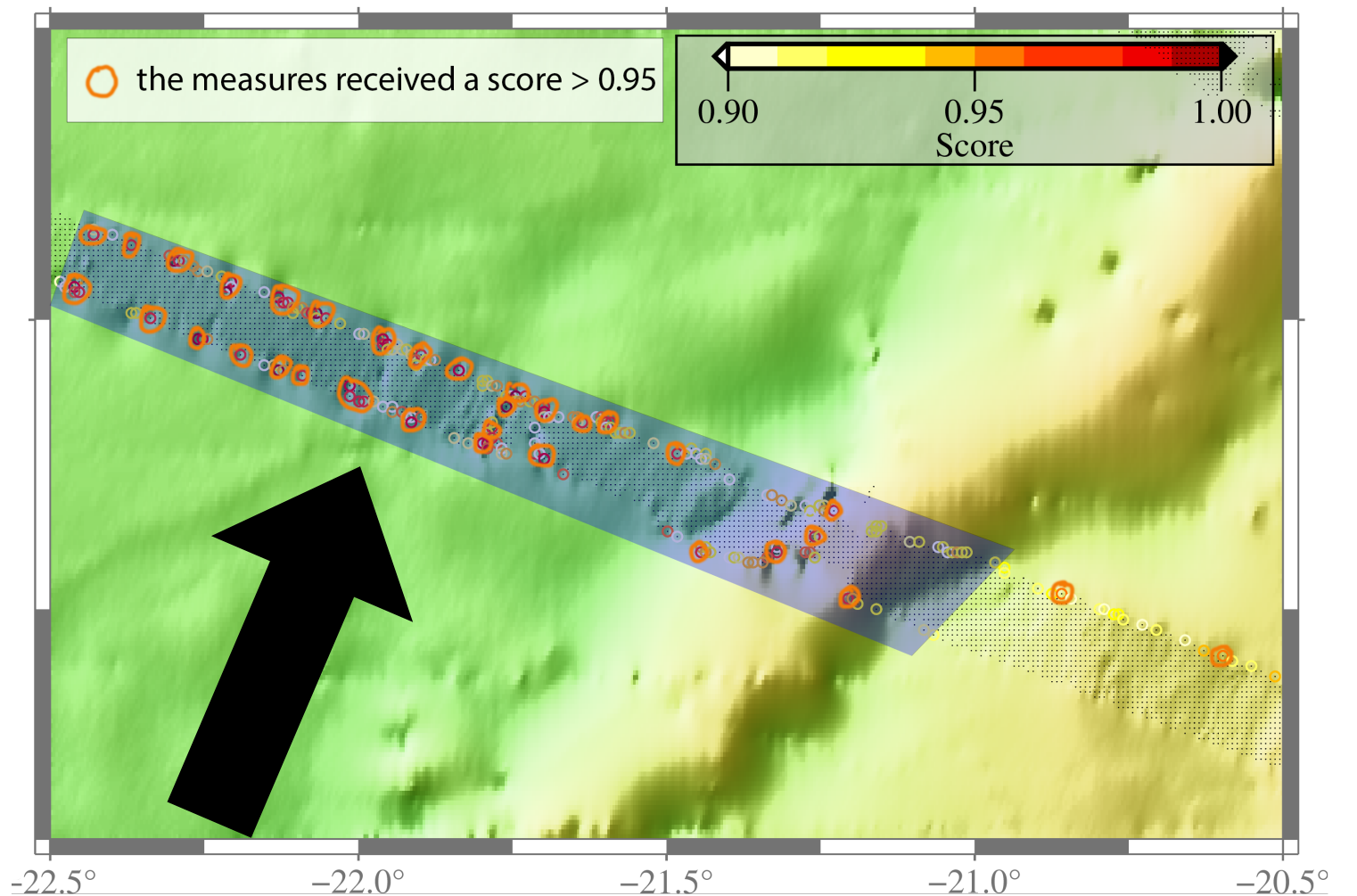
(b) Edit out corrupt measures manually



(c) Prediction scores of the ML models for bad examples



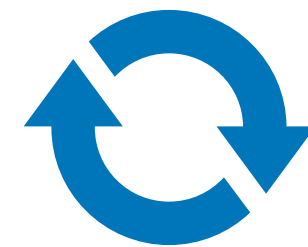
(d) Edit out corrupt measures with the ML model



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ML-aid editing + Active learning

Summary

- Using active learning reduces the workload of the human data editors
- Other lesson we learned: real-world data is (often) *non-IID*
 - As a result, randomized train/test split leads to poor generalization
- See our paper for more details: <https://arxiv.org/abs/2007.07495>