Detect slow slip events in ocean bottom pressure data using machine learning

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Detecting shallow slow slip events (SSEs) at subduction zones is important for hazard assessment as well as fault mechanics studies. However, SSE detection using ocean bottom pressure is challenging because of the low signal-to-noise ratio and instrumental drift. In this study, we adopted the 1D convolutional neural network and recurrent neural network method, trained the model with synthetic data, and detected SSEs in real bottom pressure data collected by the HOBITSS project in New Zealand.

We created synthetic data with water noise and ramp shape SSE signal. Two types of water noise, pinkish red noise and hybrid coordinate ocean model (HYCOM) are considered in this study. Each piece of data is 2-month long at hourly sampling rate. We assigned the SSE ramps with various durations (1 week to 1 month) and amplitudes (1.2-3.6 cm vertical displacement). A small linear drift is added to each piece of synthetic data to account for the imperfect de-drift process. The trained model can successfully detect an SSE and the accuracy increases with SSE amplitude. Synthetic test also shows that the machine learning model outperformed the traditional matched filter method.

We applied these two trained models to real bottom pressure data in New Zealand from July 2014 to March 2015. The model trained by pinkish red noise is more stable than HYCOM model. Both models report two events with high probability during this period. Two records are coincided well with SSEs recorded by nearby GPS stations. We conclude that our model is useful to detect SSEs in ocean bottom pressure data, even the model is trained by synthetic data.

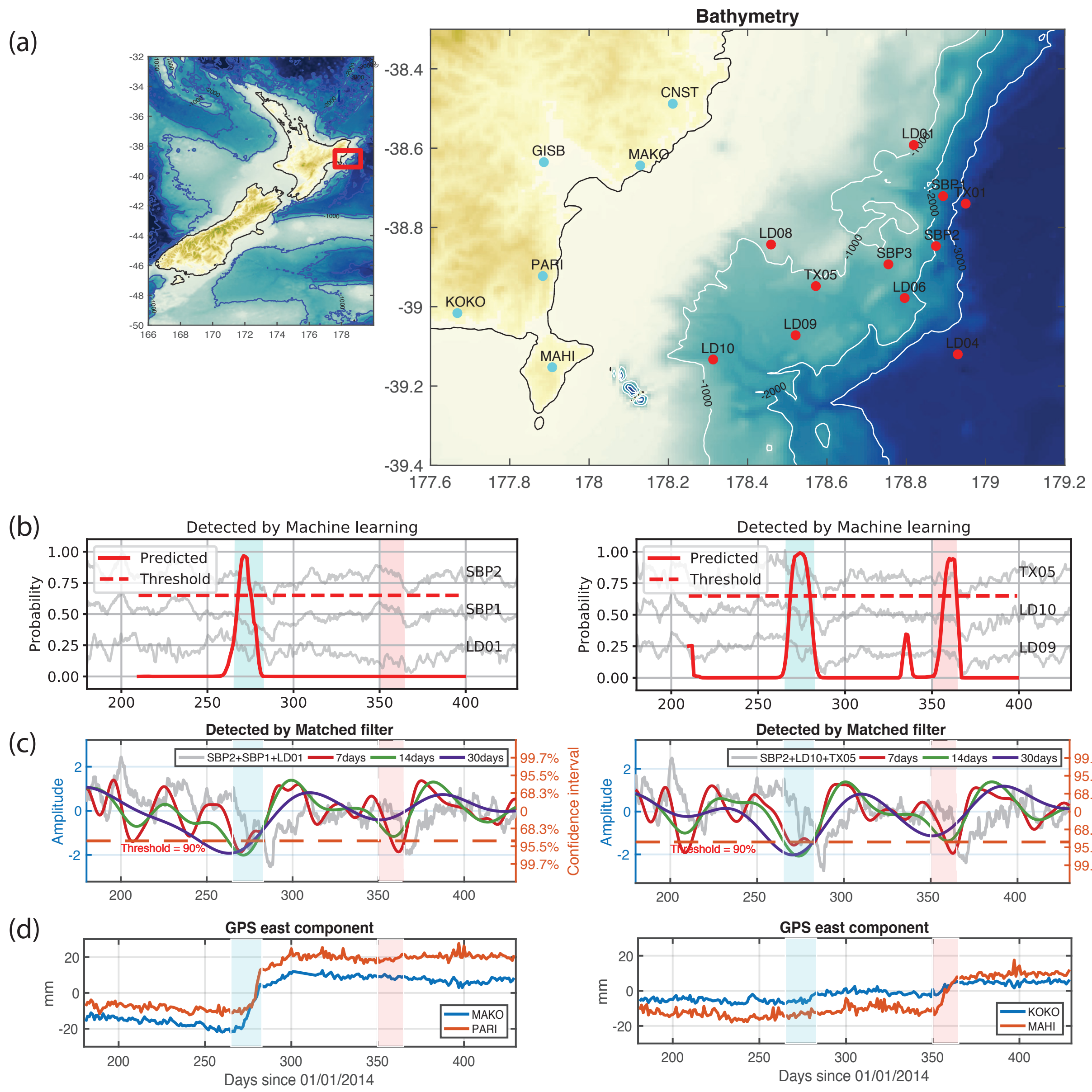

Figure caption:

(a) Study area of Hikurangi subduction zone in northern New Zealand. Red dots are HOBITSS absolute pressure gauge sites (APG) and the blue dots are onshore GPS network (www.geonet.org.nz). TX01 and LD04 are chosen as the reference sites to remove the common waves in the ocean.

(b) SSEs detected by machine learning method. Background gray lines are de-tided and de-drifted pressure difference data from three nearby APG sites. Blue and red shadows are SSEs according to the nearby GPS records. Red line is predicted result. We choose a decision threshold of 0.65 in machine learning training process.

(c) SSEs detected by matched filter method. Gray line is the stack of three pressure difference data in figure (b) Red, green and purple lines are matched filtered output using 7-day, 14-day and 30-day templates, respectively. We choose a threshold of 90%.

(d) GPS east components. Two SSEs are labeled in the data.