2021 SCEC Report

Machine Learning for Classifying Patterns of Earthquake Seismicity: Forecasting, Nowcasting, and Tsunami Early Warning - II

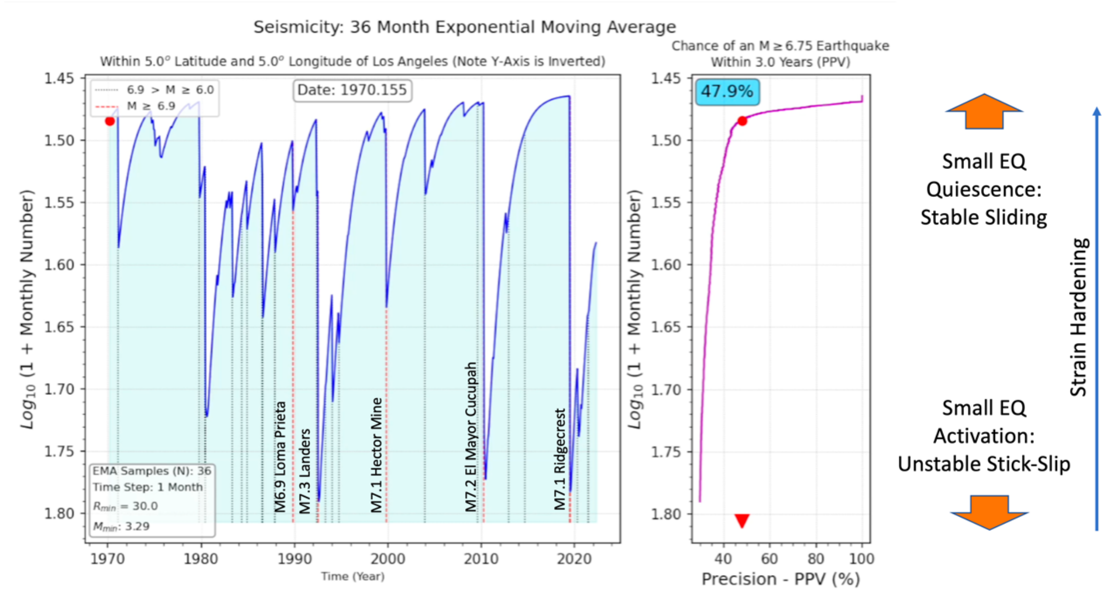
John B Rundle
Departments of Physics and Earth & Planetary Sciences
University of California, Davis, CA 95618

Earthquake Nowcasting and Forecasting with Machine Learning. Nowcasting is a term originating from economics, finance and meteorology. It refers to the process of determining the uncertain state of the economy, markets or the weather at the current time by indirect means. In this paper we describe a simple 2-parameter data analysis that reveals hidden order in otherwise seemingly chaotic earthquake seismicity. One of these parameters relates to a mechanism of seismic quiescence arising from the physics of strain-hardening of the crust prior to major events. We observe an earthquake cycle associated with major earthquakes in California, similar to what has long been postulated. An estimate of the earthquake hazard revealed by this state variable timeseries can be can be optimized by the use of machine learning in the form of the Receiver Operating Characteristic skill score. The ROC skill is used here as a loss function in a supervised learning mode. Our analysis is conducted in the region of 5^o x 5^o in latitude-longitude centered on Los Angeles, a region which we used in previous papers to build similar timeseries using more involved methods (Rundle and Donnellan, 2020; Rundle et al., 2021). Here we show that not only does the state variable timeseries have forecast skill, the associated spatial probability densities have skill as well. In addition, use of the standard ROC and Precision (PPV) metrics allow probabilities of current earthquake hazard to be defined in a simple, straightforward and rigorous way.

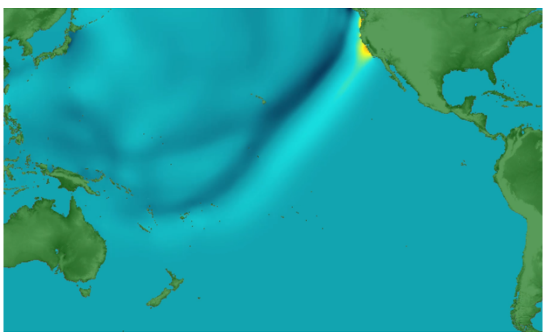
We show that a third method for computing a state variable (proxy) timeseries $\Theta(t)$ can be computed with results similar to the previous two methods. This method is by far the simplest and most transparent, involving 1) an exponential moving average of the regional seismicity, involving a number of weights N; and 2) an assumption that, as a major earthquake approaches, there is a transition in the small earthquake seismicity from unstable stick-slip to stable sliding. The latter may be due to strain-hardening or other plasticity mechanisms in crustal rocks. More specifically, the latter physics is incorporated by the assumption that there is a minimum monthly rate of small earthquakes R_{min}. These 2 parameters, N and R_{min}, are optimized in a supervised learning approach using the standard Receiver Operating Characteristic (ROC) skill score. The state variable timeseries $\Theta(t)$ can then be converted to probabilities by use of the standard Precision (PPV) computation. Both ROC and Precision are computed using a forward time window T_W = 3 years for evaluating successes (hits) and failures (false alarms). The value T_W = 3 was adopted following results in Rundle et al. (2021a,b). Finally, adopting the reasonable assumption that large earthquakes happen in or near spatial locations with large numbers of small earthquakes, (Rundle et al., 2002) we construct spatial probability density functions that complement the state variable timeseries.

An example of the result is shown in the figure below, which is one frame from a movie to be presented at SSA (2022). One of the important conclusions from this work is that there apparently is a transition from unstable stick-slip sliding early in the earthquake cycle to stable sliding as the next large earthquake approaches. We believe that this is because, for various reasons, the crust become stiffer as the earthquake cycle progresses, leading to the physics of the transition.

Movie



Precision PPV: Probability that a "prediction" of a large earthquake in a forward time interval will be a true positive TP. (PPV = TP/(TP + FP)



Tsunami Early Warning Simulations. Unlike other wave simulators, Tsunami Squares can easily propagate waves from sea to land, allowing flooded areas along the coast to be mapped. To validate its accuracy, a comparison is made to the Regional Ocean Modeling System (ROMS) tsunami simulator, which solves the Navier Stokes equations directly using a finite-difference method. The two simulation techniques show good agreement when compared over the 2011 Japan event, the 2010 Chile event, and the Indian Ocean event of 2004. Examples of inundation plots along with runup height comparisons between Tsunami Squares and observed data are displayed here to demonstrate our ability to produce accurate inundation plots for such a warning system.

At the present time, we are developing a deep learning method to compute the inundation on the Oregon coast from a hypothesized Cascadia subduction zone great earthquake. We have 29 GNSS stations as data, the idea is to use the machine learning method to rapidly estimate the runup from the tsunami, given GNSS deformation data. We compute 3000 random earthquake slip distributions, and then evaluate how accurately the runups are predicted. We train the network with gradient descent method using code from PyTorch. We use two large hidden layers. Current results show considerable promise.

Earthquake Simulators. We continue to prototype new code for our Virtual Quake simulations using our invasion percolation models, in order to greatly improve the computational efficiency of the models. In place of rectangular fault elements, we use point sources so that far more complex, and even fractal fault geometries can be addressed. So far we have shown that we can use InSAR images to invert for point source slip distributions, and that these have multifractal properties (Saylor et al., 2021). We plan to extend this type of thinking to VQ fault models using the same kind of point sources.

One idea is to replace the standard "friction law" with a failure algorithm based on invasion percolation, thus to introduce a new computationally more efficient dynamics. Using this idea, we constructed a rectangular fault with a population of pinning points on it. A pinning point breaks initially as a result of increasing "stress". Because the pinning point interacts with its neighbors, it has some (bond percolation) probability of inducing a neighbor point to break, resulting in a cascade of breaking points. There is a healing mechanism in the model as well, that allows the process to evolve and repeat. We have shown in our paper recently published in Physical Review Letters that this type of model leads to a Gutenberg-Richter type magnitude frequency relation with the correct b-value. We recently ran the model for 1 million time steps and obtained a catalog of over 10^5 events. The model ran on a fault that was split into a 50x25 (50 horizontal, 25 vertical) grid. At each time step, each unbreakable cell has a 1% chance to become breakable (they all begin the dynamics unbreakable, and reset to this state after failing) and each breakable cell has a 0.01% to fail and start an event. The bonds in this case all have a strength of 0.45, where if a randomly generated number is lower than that, it breaks. We find that indeed we find a GR scaling law as a result. One improvement that we envision is the introduction of propagation of the ruptured pinning points to neighboring faults, so that topologically realistic Virtual Quake type simulations can be readily implemented.

From Rundle et al., (2021)

JB Rundle et al., Nowcasting Earthquakes: Imaging the Earthquake Cycle in California with Machine Learning, *Earth and Space Science*, 8.12 (2021): e2021EA001757 (2021)

DP Grzan, JB Rundle, et al., Tsunami Squares: Earthquake driven inundation mapping and validation by comparison to the Regional Ocean Modeling System, submitted to *Earth and Space Science* (2022).

JB Rundle et al., Optimizing earthquake nowcasting with machine learning: The role of strain hardening in the earthquake cycle, submitted to *Earth and Space Science* (2022)