Towards physics-based earthquake forecasting: making new observations or developing a model testing framework

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Overview

Current earthquake hazard estimates are primarily empirical. To first order, they assume that earthquakes occur where they occurred before. However, forecasts are increasingly incorporating more physical constraints. Some models include information about faults' geological slip rates and about inter-earthquake triggering.

However, there are *many* more physical constraints that we could use. For instance, swarms of small earthquakes sometimes indicate an acceleration of the underlying fault, which can lead to large earthquakes (e.g., Kato et al, 2012; Rouet-Leduc et al, 2019). And when the fluid pressure in the subsurface increases---perhaps because we have sequestered CO_2, earthquakes can initiate more easily.

Incorporating such physical constraints into earthquake forecasts will require us to overcome several challenges. First, if we are to forecast the evolution of complex fault zones, we to map those fault zones, and we need numerous observations of a range of properties. Second, we need to use those observations to assess physical models---to determine faults' conditions and potential to produce large earthquakes.

In this PhD project, you may make some of the first steps toward addressing these challenges.

Option 1: Developing novel observations

First, you may develop rapid observations to constrain the properties of subsurface fault systems. The most common observations are small earthquake timing and location, and you may wish to begin there.

However, additional information could come from

- Earthquake stress drops
- Earthquake rupture extent
- Local pore pressure or seismic velocity
- Ambient seismic "noise," which could come from tiny earthquakes.
- Other signals you think could be relevant for earthquake activity

You will develop new techniques to rapidly map each of these properties, using particular combinations of the data to probe locations close to the fault and employing machine learning tools to speed up and simplify the analysis.

Then you will interpret your results in the context of local changes in seismicity. For instance, if you focus on the Costa Rican subduction zone, you may assess whether ambient seismic noise increases before large earthquakes or after slow slip events. Or if you focus on a CO_2 injection site, you may examine how local seismic velocities change as pore pressure is increased.

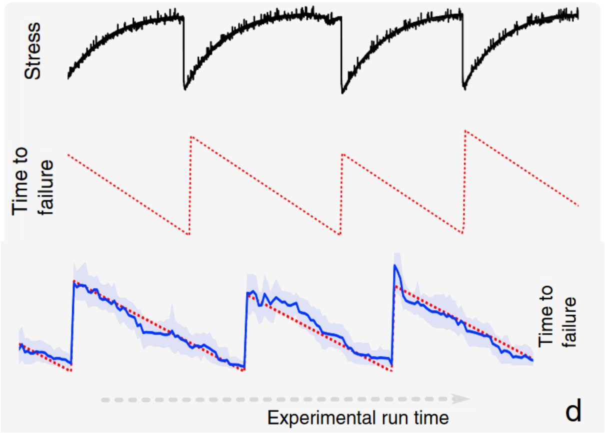
You will assess how numerous but quickly made observations can tell us about the fault conditions and seismic hazard.

Option 2: Mapping observations to model conditions

Our ultimate goal, however, is to create thousands of earthquake forecasts, for thousands of locations around the world. With that goal in mind, we do not want to interpret each set of observations manually. We want a robust framework that can use numerous observations to map the current state of the fault network and forecast its future behaviour---like a weather model, but for earthquakes.

Of course, creating a complete forecast is beyond the scope of a single PhD, but you will create a framework to combine the model conditions and observations. You may start with a simplified laboratory setup of earthquakes: a sliding block.

Stress on the block gradually builds up and is then released in “earthquakes,” as shown below.



Stress and time to failure in an experimental spring block slider, by Rouet-Leduc et al, 2017. They have developed a random forest model to predict the time to failure: the time to the next earthquake.

You may attempt to forecast the timing of laboratory earthquakes using not just the observations, as has been the focus of previous work (e.g., Rouet-Leduc et al, 2017), but also physical constraints; we know how stress is related to the block’s slip rate, for example.

You may take one of several approaches to constrain the physical properties of the fault system and to forecast future earthquakes. Perhaps a neural network that maps observations to fault properties and then to slip times would be sufficient. Perhaps a Bayesian graph model would be more flexible. Or perhaps the datasets are large enough that we should create a neural network to represent the physical model and then train that network with observations. You might be interested in forecasting that works by exploiting the dynamics of the (black-boxed) system, to learn how this system evolves (Chakrabarty, 2023).

As you develop the framework, you may take the model in of several directions: perhaps focusing on what we can learn about the rheology by imposing a flexible model, or perhaps considering more complex systems, including simulations of earthquakes on extended faults.

Timeline

Years 1-2: initial observations and technique development, primary model development, identifying physical questions

Years 2-3: further analysis and technique development, extraction of key features, physical modelling and interpretation

Training & Skills

You will learn a range of seismological techniques, as well as in general time series analysis methods, in order to robustly analyse the seismograms. Depending on your focus, you may also develop your abilities in physical oceanography or in machine learning. You will likely attend classes or summer schools and follow self-developed reading courses or journal clubs with your working groups.

Depending on interest, there are various possibilities for collaborations within Oxford and with researchers at other institutions in the UK, US, and Europe. You will interact with researchers working models and on geological and geophysical observations and will attend conferences and workshops in the UK, Europe, and the US.

Finally, you will develop your ability to write and present your work so that you can have more fruitful interactions your colleagues.

References & Further Reading

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Further Information

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This project would be suited to a student interested in seismic hazard and physical understanding of the Earth, with an ambition to approach complex datasets. Such a student could have a wide variety of backgrounds, from geology to physics, engineering, or computer science. There will be opportunities to further develop your knowledge in unfamiliar areas. Please get in touch if you're interested in a project along these lines.