The physics of earthquake forecasting

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The Coulomb stress theory is the basic physics principle upon which scientists rely for improving our understanding behind earthquake triggering processes and therefore, our predictability of future earthquake hazards. The assumption that following a large earthquake the expected regional stress redistribution will affect other faults has been known since the late 19th century and has been passed on for further consideration by Charles Richter. However, we still struggle to define its implementation principles in short-term forecasts. This opinion paper discusses the recent advances in physics-based earthquake forecasting to motivate an open discussion about what we have collectively learnt from the last 30 years of published research on physics-based forecasts and where future experiments should aim.

If one considers that seismologists are aware of the connection between stress redistribution effects and seismicity response for decades, if not a century, then it is surprising that there is such a slow pace in understanding the physics of earthquake triggering. Looking at the rapid advancement of statistical forecasting, which was conceptualized by Ogata (1985, 1988*a,b*) and now is the reference mathematical approximation of earthquake triggering processes, then one would argue that physics had quite a head start but somewhere along the way slowed down.

So what is so challenging in the realization of Coulomb stress theory? Is it implementation challenges, such as the different input data products required, or our limited understanding of earthquake triggering mechanisms? Segou and Parsons (2020) looked into past implementations while focusing on a systematic reassessment of Coulomb stress theory using the data-rich M=7.2 El-Mayor Cucapah sequence. The evaluation of past hypotheses motivated the development of a new technique to forecast rupture styles of triggered seismicity.

In the mind of the seismologists working on the issue today elastic stress redistribution equals Coulomb stress change estimates. In the early 90s there was an enthusiasm that the basic principle, namely *coseismic stress changes*, is the accurate operator for large magnitude aftershock prediction (Stein, 1999). More complex ideas were proposed supporting the role of the regional stress field priming the well-oriented for failure faults while still attributing aftershock occurrence solely to coseismic stress changes (King et al., 1994). Two major assumptions were passed on from these early influential works; firstly, a coseismic stress triggering threshold of 0.01 MPa is required (Harris and Simpson, 1992) and secondly, the most hazardous faults in evolving aftershock sequences are the ones that maximize stress (King et al., 1994). The 1992 M=7.3 Landers cascade revolutionized not only the way seismologists thought about local aftershock patterns but also about remote dynamic triggering; in a seminal work Hill et al. (1993) described the far reach of this mainshock that increased seismic activity across much of the western United States. Around the same time the rate-and-state laboratory-confirmed law brought continuum mechanics into aftershock forecasts by describing triggered seismicity as a response to these estimated stress perturbations (Dieterich, 1994).

By the early 2000s, scientific research related with remote dynamic triggering (e.g. Prejean and Hill, 2009) and borehole breakouts (Townend and Zoback, 2004) revealed that even minuscule stress changes from teleseismic waves can trigger seismicity and that crust is always in a critical state even in low strain rate intraplate regions, respectively. These results imply that active faults anywhere in the crust balance at the cusp of failure and even the smallest stress perturbations will lead to failure. A few years later the improvement of regional networks allowed for global studies on remote dynamic triggering (e.g. Hill and Prejean, 2015) revealing that the magnitude of peak dynamic stresses is not the controlling factor behind triggering potential but the orientation of regional faults with respect to backazimuth of incoming waves play an important role in susceptibility (Parsons et al., 2014). More complex observations related to microearthquakes (Aiken and Peng, 2014) and tremor triggering suggested that low effective stress results in a relatively low triggering threshold around 2-3 kPa in central California (Peng et al., 2009). No matter how provocative these findings were, and still are, they did not change the implementation of Coulomb stress theory.

Without a doubt the Regional Earthquake Likelihood Models (RELM) experiment (Schorlemmer et al., 2007) and the Collaboratory of the Study of Earthquake Predictability (CSEP; Zechar et al., 2010) motivated modelers to put forecast models under prospective testing tied with predefined performance evaluation metrics. Also, the challenges in scientific communication and testable forecast development came into the light in the post-2009 L'Aquila disaster environment (Jordan et al., 2011). Nowadays, the operational earthquake forecast system in Italy (Warner et al., 2014) exemplifies the scientific advantages of prospective testing and its contribution to decision-making protocols (Marzocchi et al., 2015). The majority of submitted models correspond to statistical forecasts; a fact that is mostly related to practical challenges behind the standardization of input data formats and computer code development. Perhaps the next phase of CSEP will look into these matters since the recent New Zealand experiment (Michael and Werner, 2018) and research projects underway, such as the NSFGEO-NERC funded *The Central Apennines Under A New Microscope* and the EU funded *RISE*, stimulate further the interest for physics-based forecasts.

The above initiatives promoted the development of physics-based models up to the point that within few years regional and sequence-specific comparative testing revealed that these models present comparable to better performance than ETAS forecasts (Segou et al., 2013; Segou and Parsons, 2016; Cattania et al., 2018; Mancini et al., 2019). The recipe for the best physics-based forecast is somewhat expected; realistic heterogeneous in geometry faults, secondary triggering effects, optimization of model parameters, use of *best-available* (vs. early) data products. The last two are challenges that statistical catalog-based models also faced and partly addressed (e.g. Omi et al., 2014).

Outside of the common challenges, the limitations of stress models are somewhat different and often not discussed in recent literature. In physics fault-based approaches the expected seismicity rate corresponds to nucleations on a specified fault geometry. The modelers eventually compare fault-specific expected rates (e.g. on strike-slip faults) against observed seismicity belonging to diverse populations. Addressing this limitation Segou and Parsons (2019), in a 3-yr retrospective sequence-specific experiment, used available past focal mechanisms as spatially-variable receivers under a spatially-varying stress field asking the question, *Do earthquake occur on the idealized planes that maximize coseismic stress or they rupture pre-existing ones?* They found that at a 0.89 majority occurs on pre-existing ruptures. This simple consideration of small-scale diverse-style faults is directly linked to the realization of critical stresses in the crust. The fact that the well-expressed large-scale parallel faults present negative coseismic stresses at the same time means that a small-scale spatial rearrangement of stresses takes place on the diverse fault populations. Putting this concept into a pseudo-prospective mode Mancini et al. (2019) represented off-fault small scale heterogeneity coupled with secondary triggering effects in the 2016-2017 Central Apennines sequence leading to higher information gain per earthquake on behalf of physics-based models against the statistical reference model. The second challenge is the relationship between the coseismic stress changes amplitude and the expected seismicity response. This touches upon the persisting problem of earthquake occurrences in the shadow zones. An alternative explanation is now found when looking into the total stress estimates. However, the surprise comes when Segou and Parsons (2020) queried whether the theoretical maximum total stress plane corresponds to the triggered plane(s). They found this to be correct only for the 0.18 of triggered seismicity within the first few months of the sequence. The above findings on the efficiency of the maximum stress criterion remove some certainty from seismologists about which faults are immediately hazardous during an evolving earthquake sequence. Indeed, high expected rates on low-stressed *misoriented* faults following a mainshock raise concerns. The 2019 M7.1 Ridgecrest earthquake has stress loaded the Garlock Fault (Mancini et al., 2020) but so far the latter exhibits only shallow creep and swarm-type occurrences (Ross et al., 2019). The recent 2018 California test of the 1998-issued 30-yr earthquake probabilities forecast revealed that only the 2004 M=6.0 Parkfield earthquake was "unambiguously connected with the forecast outcome" with better estimates provided by an improved model (Jackson, 2018).

The encouraging results from the consideration of the total stress estimates in Segou and Parsons (2020) should be extended to incorporate localized triggering contributions from background seismicity, stress patterns within unfolding sequences and random-noise stress perturbations accounting for dynamic triggering effects but perhaps the most challenging is to describe spatially-varying stressing rates in the fine-scale of forecast experiments. Those considerations will help us map potential delayed responses within a decadal time scale over complex fault patterns that are now imaged in greater detail than ever before (Ross et al., 2019). Admittedly the controlling factor behind our collective progress is the expansion of seismic networks and the implementation of techniques, such as the double-difference relocation, aided by waveform cross-correlation, (e.g. Waldhauser and Ellsworth, 2000) and template matching (Peng and Zhao, 2009), that shaped our capability to detect and characterize earthquakes in high seismic hazard regions, such as California, Italy, Japan, and New Zealand. Recently deep learning techniques (Mousavi et al., 2019) introduce novel workflows that revolutionize our image of earthquake activity with real-time implementation in sight. In cases of seismicity induced by industrial injections enhancing network detection capability will support decision-makers and operators (Zhang et al., 2019). It remains to be seen whether the physics-based models employing artificial intelligence (AI) catalogs will outperform AI-driven forecasts (e.g. DeVries et al. 2018).

Moving forward new performance tests that will evaluate the impact of the aforementioned limitations in stress-based models should be introduced but also more physics has to come into play. The integration in physics-based models of slow earthquakes and postseismic, dynamic triggering and poroelastic effects should not be ignored. These phenomena control earthquake physics over different time scales and that by itself is a challenge. How do we reconcile between short, intermediate and long-term forecasts? Do we need new ideas? Segou and Parsons (2020) presented a new technique for mapping triggering potential but stills expanding our testing in a decadal time horizon requires heavy borrowing from rate-and-state simulators tasked at the moment at significantly longer earthquake cycles. Any new ideas should present a unified explanation of induced to remotely triggered seismicity observations in different spatial and temporal scales. However, describing our model's failure from understanding the reasons behind the poor performance is not the same task.

There is no doubt that statistical ETAS forecasts provided the first quantification of predictive skills and that they carry a whole lot of physics that we do not fully appreciate at the moment. They are clever, catalog-based, globally accepted with a simplicity that invites transparency, comparability, and reproducibility. The empirically-driven statistical mathematics behind the estimation of a probability for any natural occurrence remains within the realm of Physics-at least according to the rationale behind the 1921 Nobel prize nomination committee for Physics in support of the statistical mechanics nominee (Isaacson, 2009).

Recent advances in ETAS model (Field et al., 2017) supported a more fault-based character while secondary triggering effects make stress-based forecasts more ETAS-like (Mancini et al., 2019). Therefore, there is room for exchanges of the advantageous traits of each model and perhaps the key in operational forecasting is doing exactly that—combing them in time and space while avoiding the devious course of overfitting (Warner et al., 2012). Marzocchi and Jordan (2018) presented a probabilistic framework for testing forecasts of earthquake probabilities showing how different experimental concepts can probe specific model features. The contribution of CSEP group towards an even more inclusive and well-designed testing protocol that will reveal any significant information gain behind physics-based simulations would require the extension of data input formats, computational resources and the introduction of additional performance metrics.

Clearly, the road ahead for the next generation of physics-based models is far more difficult but we have to also recognize what we are asking of them, and that is to inform us about the complex physical mechanisms of earthquake triggering. That's not an easy or trivial task.

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