Incorporating induced seismicity source models and ground motion predictions to forecast dynamic regional risk

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ABSTRACT

Decision-making regarding induced seismicity benefits greatly from quantitative risk assessment. While seismic hazard and risk analysis is widely used for natural seismicity, unique aspects of induced earthquakes require new tools to estimate occurrence rates of future earthquakes, to understand unique features of resulting ground motions, and to understand potential consequences at a regional scale. In this paper, we highlight recent work in dynamic source characterization and induced seismicity ground motion prediction to determine the hazard in the area, followed by prediction of regional scale risk. Results can be used to forecast risk under potential future earthquake activity, to predict benefits of potential interventions, and to quantify important uncertainties in the model that could be refined with further study. Example results for the State of Oklahoma are used to illustrate the potential insights from this analysis approach.

INTRODUCTION

Risk analysis is a well-established framework for assessing potential impacts of a range of human activities, evaluating the acceptability of those impacts, and taking actions to manage risks. For natural seismicity, risk assessment and hazard assessment are widely used and well established (e.g., McGuire 2004; Petersen et al. 2014). As induced seismicity has emerged as an important issue in a number of regions of the world, adoption of these approaches has naturally arisen as a potentially important tool to support decision-making (e.g., Bommer et al. 2015; Herrmann et al. 2016; Mignan et al. 2015; Walters et al. 2015). Induced seismicity, however, has several unique aspects that make adoption of standard hazard and risk analysis approaches non-trivial. This manuscript thus highlights several recent developments that enable improved assessment of risks from induced seismicity.

The first challenge with induced seismicity is that the long-term rate of earthquake activity is not constant. For natural seismicity, we typically examine time scales where the crustal stressing process are assumed to be constant, such that past earthquake rates and past straining rates are representative of the future. With induced seismicity, earthquake activity is understood to accelerated by anthropogenic processes (e.g., pore pressure perturbations due to fluid injection, which changes the conditions needed to initiate an earthquake rupture). Induced earthquake activity rates are seen in some cases to vary dramatically on the scale of years or even days. Thus, the estimation of future earthquake activity rates requires more than simply computing average earthquake rates over the window of available past data. One solution for this issue is to estimate seismicity rates in narrow windows of time (Atkinson et al. 2015; Convertito et al. 2012; Mignan et al. 2015; Petersen et al. 2016, 2017). Statistical seismicity models can also produce short-term dynamic estimates of earthquake activity at well-instrumented sites (e.g., Ogata 1988; Werner et al. 2011), but they are less directly applicable when locations of potential seismicity are not well characterized, the region is sparsely instrumented, and it is difficult to locate or even detect the small earthquakes that indicate potential occurrence rates of large earthquakes (Ellsworth 2013).

A second challenge is the prediction of ground motions for a given earthquake scenario. Given the limited historical natural seismicity in many regions experiencing induced seismicity, the uncertainty about how induced earthquakes may differ from naturally occurring earthquakes, the importance of ground motion predictions in understanding risk of damage to the built environment, characterization of ground motions remains an important topic (Petersen et al. 2017). A final challenge is integration of seismicity, ground motion and vulnerability information to assess risk, in a manner that is informative but also dynamic in order to support real-time analysis and decision-making (e.g., Herrmann et al. 2016; Walters et al. 2015). In the following sections, we briefly highlight some recent work by the authors to address the above challenges.

DYNAMIC ESTIMATION OF SEISMICITY RATES

A general solution to the challenge of dealing with potentially-increased seismicity rates is to apply a prior distribution to earthquake rates, which is consistent with historical seismicity but also allows for the possibility of a rate increase due to anthropogenic factors. Bayesian statistics are quite useful for this approach, as they can allow for use of a prior distribution for potential future changes in seismicity parameters. A likelihood function can then specify how observational data can be used to indicate occurrence of such an increase, and the posterior distribution integrates these factors.

A change point model is one potential implementation of this type. This model assumes that earthquakes occur as a Poisson process with rate λ_1 up to time τ, and after that occur as a Poisson process with a new rate λ_2. The three parameters are unknown, with λ_1 and λ_2 having diffuse prior Gamma distributions and τ a uniform (over the duration of the catalog) prior distribution. For a given λ_1, λ_2 and τ, a likelihood function can be formulated and a posterior distribution computed using numerical integration (Raftery and Akman 1986; Gupta and Baker 2015). The model also includes a model selection step to determine whether observational data is more consistent with a constant rate (i.e., no change in seismicity) or a change point. A Bayes factor, the constant rate likelihood divided by the change point likelihood, is integrated over the posterior distributions and used to evaluate which model is more suitable for a given catalog (Raftery and Akman 1986).

A key advantage of this approach is that the rate estimation is fully automated, requiring only an input stream of earthquake event occurrences. A change in earthquake rates can immediately indicate an increase in seismic risk. For example, from Time A to Time B in Figure 1a, three earthquakes are observed over an 11-month span (versus three earthquakes in the prior 35 years); the Change Point evaluation indicates a changed rate, and the estimated rate immediately increases by more than an order of magnitude (Figure 1c). This change in rates is visibly apparent after several years of earthquake occurrences with increased rates, and could now be manually estimated using judgement, but the automation of the process is important for truly dynamic hazard analyses to be feasible, and to be useful in supporting decision-making.

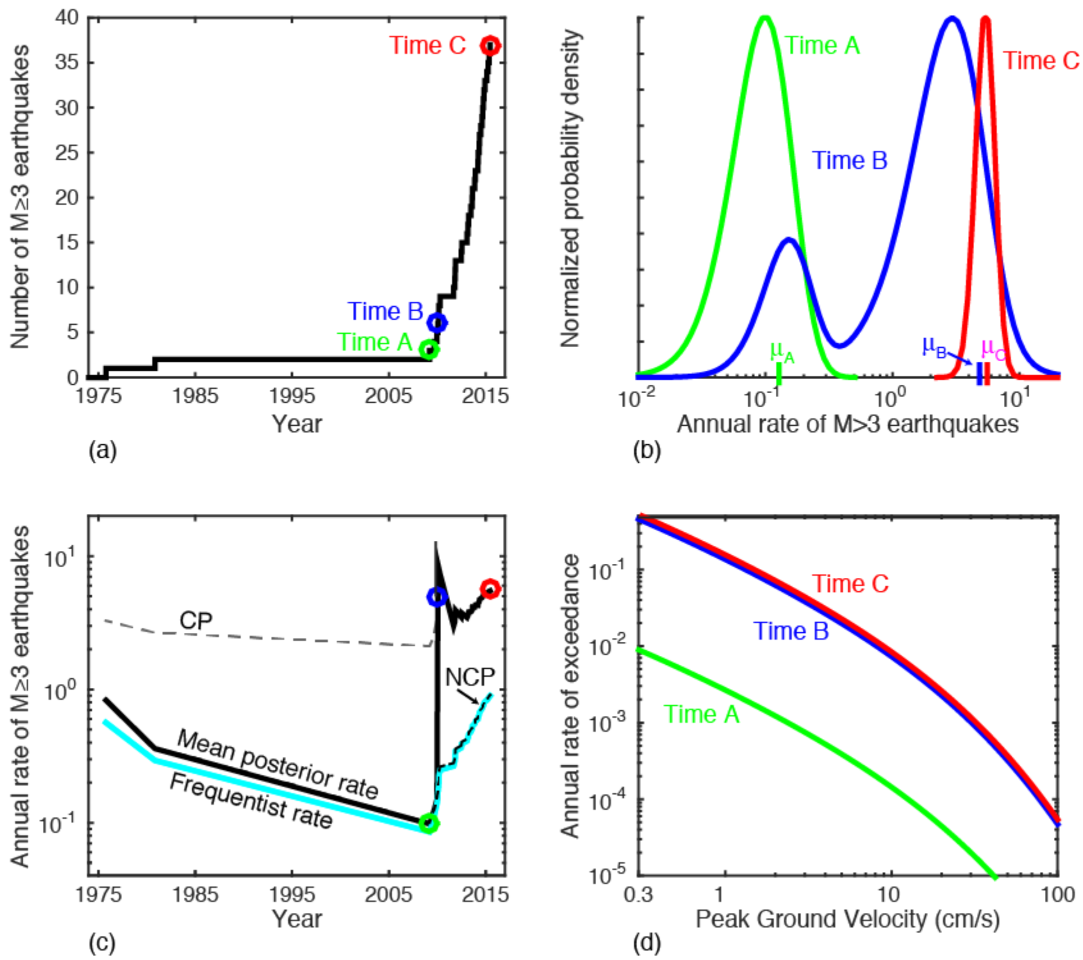

Figure 1. (a) Cumulative number of observed earthquakes within a 25 km radius of Oklahoma City. (b) Posterior earthquake rate distributions at three selected points in time. (c) Mean posterior earthquake rate and frequentist rate versus time. The dashed lines

labeled CP and NCP are the mean posterior rates assuming a change point or no change point, respectively. (d) Mean hazard curves given the posterior earthquake rates at the three selected points in time. Figure from Baker and Gupta (2016).

In general, seismicity rates needed for hazard and risk analyses will vary spatially as well as temporally. To add the spatial component, the earthquake catalog can be gridded and the above Change Point calculation can be performed for the catalog associated with each grid point. The Gridding of data requires some spatial window. Gupta and Baker (2017) specify this approach, and explore how to select an appropriate spatial window using validation on future earthquake events (i.e., earthquakes observed in the actual present, but in the future relative to the catalog used for parameter estimation). For the Oklahoma earthquake catalog through 2015, a spatial radius of approximately 25 km was found to be most predictive in estimating earthquakes following the catalog window used for the initial fitting.

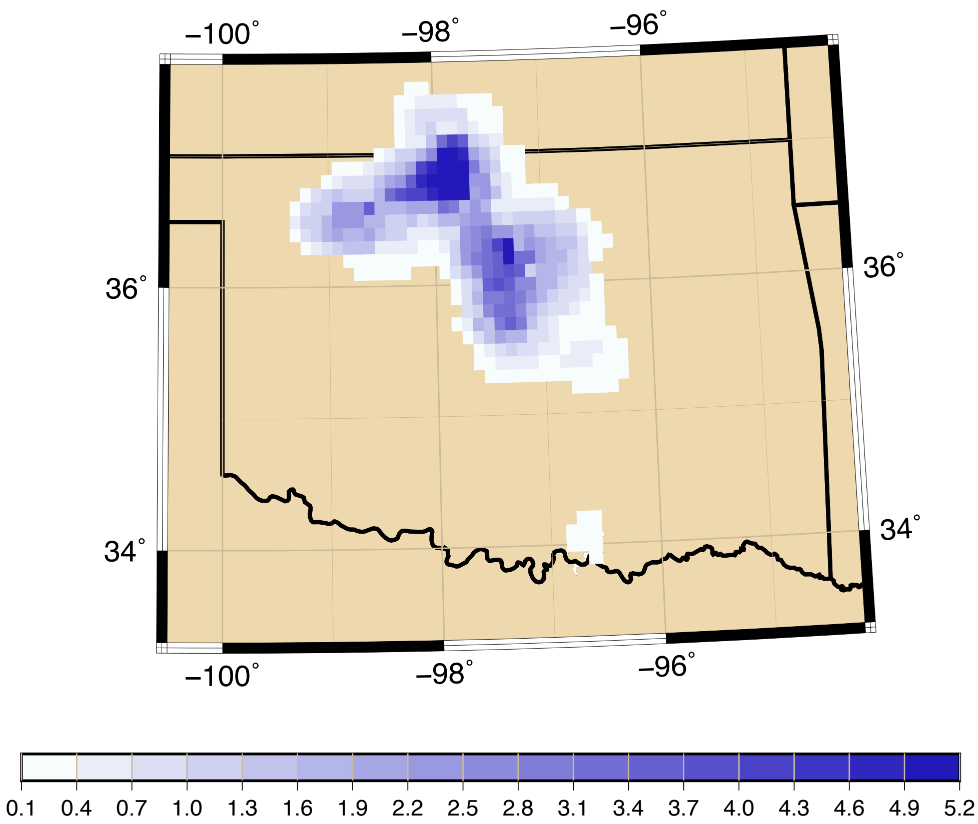

Figure 2. Annual rate of M ≥ 3 earthquakes per 100 km^2, estimated using spatially varying Change Point calculations and an earthquake catalog extending from January 01, 1974 to December 31, 2015 (from Gupta and Baker 2017).

GROUND MOTION PREDICTION

A number of researchers have recently developed ground motion prediction models for the Central and Eastern United States, to account for potential unique aspects of induced earthquakes--primarily the typically-shallower depths, and potentially unique aspects of source and site properties (Atkinson 2015; Bydlon et al. 2017; Gupta et al. 2017; Hassani and Atkinson 2016; Shahjouei and Pezeshk 2016).

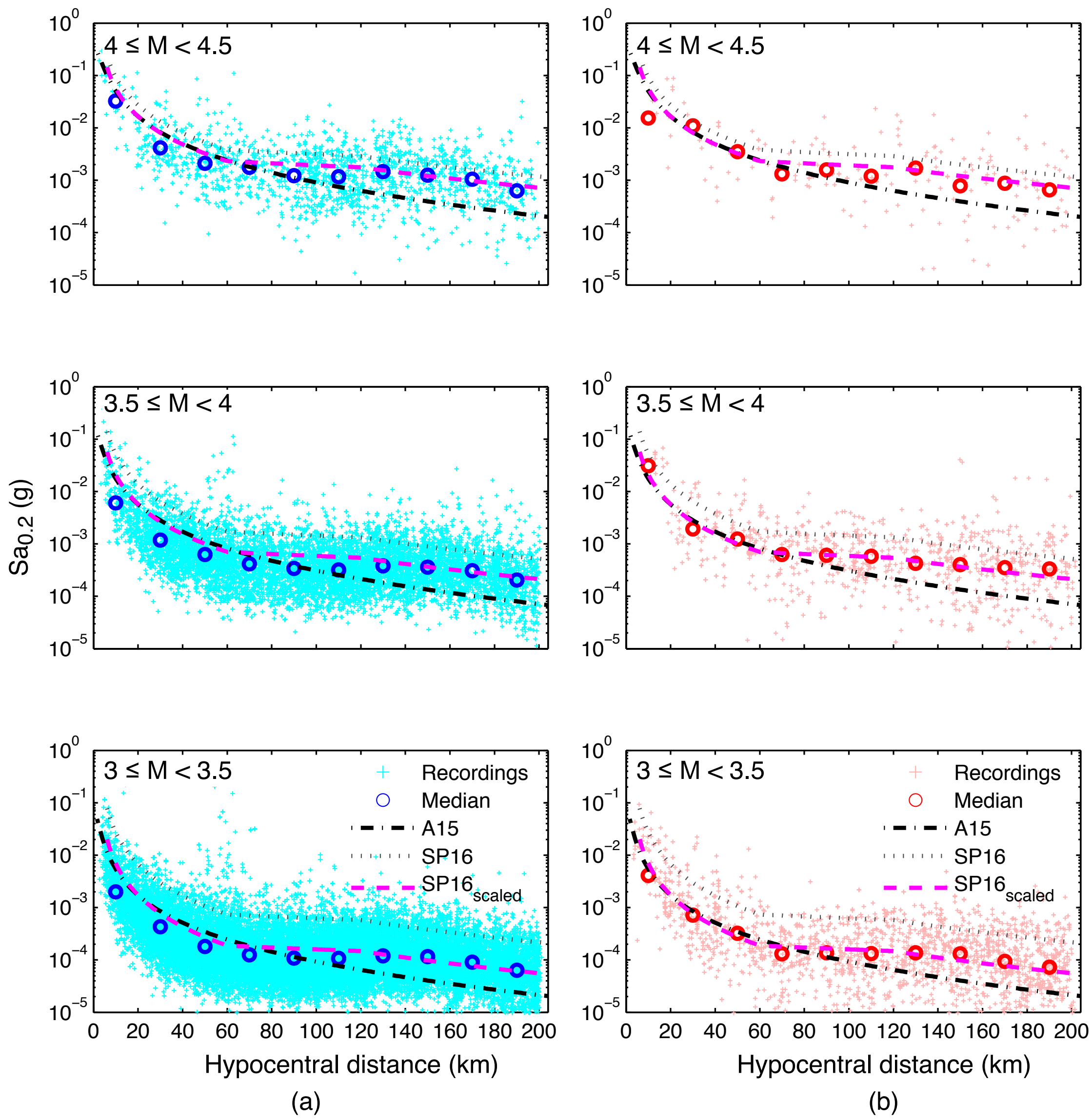

Figure 3. Observed spectral acceleration values at a period of 0.2s ($S_{a0.2}$) from ground motions recorded in the Central and Eastern United States, and Median predictions of these ground motion amplitudes. Circles indicated medians for ground motion sets binned by distance, dash-dot lines indicate predictions from Atkinson (2015), dotted lines indicate predictions from Shahjouei and Pezeshk (2016) and dashed lines indicate predictions from

the scaled model of Gupta et al. (2017). The left figures are for ground motions in the space-time windows specified by the UGSS as having potentially induced earthquakes (Petersen et al. 2016), and the right figures are for all other ground motions. Figure from Gupta et al. (2017).

Figure 3 shows example results from the empirical study of Gupta et al. (2017). That study observed that the ground motions from potentially induced earthquakes (primarily from earthquakes in Oklahoma, Texas and Kansas) appeared to decay faster in amplitude with distance than natural earthquakes, at distances of less than 20 km. It also suggested that natural earthquakes elsewhere in the Central and Eastern US had somewhat larger amplitudes than the potentially induced ground motions at distances of greater than 60 km. Despite the relatively large set of ground motions from that study (46,178 recordings) constraints at large magnitudes and small distances are still relatively weak, and so numerical studies or site-specific studies are likely the most promising for developing a deeper understanding of these issues (e.g., Bommer et al. 2016; Bydlon et al. 2017).

DYNAMIC RISK ANALYSIS

With earthquake activity rates dynamically characterized, a suitable approach for ground motion prediction, and information about the assets at risk and their vulnerability to shaking, we can then assess risk of damage and understand how it changes in time.

The annual rate that losses exceed some amount can be computed as follows

$$\lambda(Loss > x) = \sum_{i=1}^{n_{rup}} \iiint_{\mathbf{IM}} P(Loss > x|\mathbf{IM}) f(\mathbf{IM}|rup_i)\, d\mathbf{IM}\, \lambda\,(rup_i) \tag{1}$$

where *Loss* is the loss (financial or otherwise) to a portfolio of assets, $\lambda(Loss>x)$ is the annual rate of loss exceeding some loss threshold x. n_{rup} is the number of earthquake sources considered, rup_i is an earthquake rupture scenario (e.g., a source extent and magnitude), $\lambda(rup_i)$ is the annual rate of occurrence of that rupture, **IM** is a vector of ground motion intensities at all locations of interest, $f(\mathbf{IM}|\, rup_i)$ is the joint probability density function of **IM**, given a rupture rup_i, and $P(Loss>x|\mathbf{IM})$ is the probability of exceeding the given loss level, conditional on occurrence of ground motions with intensity **IM** at the locations of interest. In the induced seismicity case, $\lambda(rup_i)$ will be changing over time, and can be estimated using the techniques introduced above.

Figure 4 illustrates results from such an analysis. This figure reports the loss level estimated to be exceeded with a 10% probability in a given one-year period, where the results vary with time, with earthquake rates, sizes and locations based on the spatio-temporal Change Point rate estimation described above. Ground motion prediction is performed using the model of Gupta et al. (2017), with spatial correlation of amplitudes considered. Building locations, occupancies, building types, values and associated vulnerability models (using one-second spectral acceleration) are all from HAZUS (FEMA 2015). The asset exposure is assumed here to be static over time, but if desired could also be dynamic to reflect changes in the built environment over time (Lallemant et al. 2014). The results were produced using the OpenQuake engine (Pagani et al. 2014).

Figure 4 shows that for Oklahoma, risks increased from essentially zero prior to 2009, to substantial levels in the past few years. The risk has been decreasing recently, but not as quickly as the overall statewide rate of earthquake occurrence. This slower decrease indicates that the earthquake rate decreases are happening disproportionately in the regions of the state with lower exposure (i.e., far from big cities) and so there is not a proportionate risk reduction with the earthquake rate reduction. The figure also likely indicates higher risk than has actually been present in recent years; there have been several M>4 earthquakes in the state that have caused total losses in the 10's of millions of dollars, but apparently none in the hundreds of millions, which would be unlikely given the Figure 4 predictions of ~$400 million dollar losses with 50% annual probability for a several-year period. Ongoing work is studying whether this is due to the HAZUS vulnerability functions over-predicting damage for a given shaking, over-estimation of ground motion amplitudes, or some other reason. Whether the specific risk numbers change or not, however, the results indicate that dynamic analysis of risk from induced seismicity is feasible.

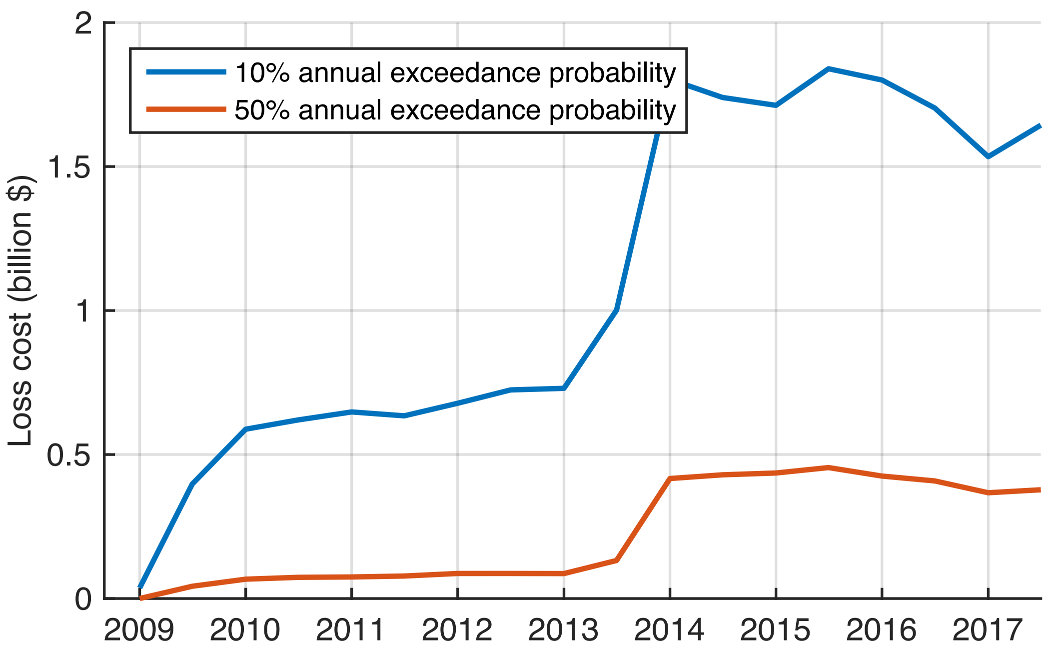

Figure 4. Time-varying risk analysis results for statewide losses in Oklahoma (Gupta 2017).

CONCLUSION

The time-varying nature of induced seismicity, and its occurrence in regions with low rates of natural seismicity, lead to challenges in characterizing potential future earthquake activity for the purposes of assessing hazard and risk. Nonetheless, statistical approaches that account for these unique issues can be developed so as to facilitate the use of risk analysis tools. Further, if the dynamic aspects of the problem are addressed using models that are automatic in incorporating new data (e.g., Bayesian models), then risk metrics can be evaluated in real time and used to support decision-making. Further opportunities with these approaches lie in incorporating other data besides observed seismicity, such as incorporating seismicity predictions based on fluid injection processes, so as to better predict the impact of actual or potential changes in fluid injection (e.g., Gupta 2017; Langenbruch and Zoback 2016).

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