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1 **Examining the capability of statistical models to**
2 **mitigate induced seismicity during hydraulic**
3 **fracturing of shale gas reservoirs**

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ABSTRACT

Injection into the subsurface is carried out by industry for a variety of reasons: storage of waste-water; enhanced oil recovery; and for hydraulic fracture stimulation. By increasing subsurface pressures, injection can trigger felt seismicity (i.e. of sufficient magnitude to be felt at the surface) on pre-existing faults. As the number of cases of felt seismicity associated with hydraulic fracturing has increased, strategies for mitigating induced seismicity are required. However, most hydraulic stimulation activities do not induce felt seismicity. Therefore a mitigation strategy is required that is capable of differentiating the “normal” case from “abnormal” cases that trigger larger events. In this paper we test the ability of statistical methods to estimate the largest event size during stimulation, applying these approaches to two datasets collected during hydraulic stimulation in the Horn River Shale, British Columbia, where hydraulic fracturing was observed to reactivate faults. We apply these methods in a prospective manner: using the microseismicity recorded during the early phases of a stimulation stage to make forecasts about what will happen as the stage continues. We do so to put ourselves in the shoes of an operator or regulator, where decisions must be taken based on data as it is acquired, rather than a post hoc analysis once a stimulation stage has been completed. We find that the proposed methods can provide a reasonable forecast of the largest event to occur during each stage. This means that these methods can be used as the basis of a mitigation strategy for induced seismicity.

32 INTRODUCTION

33 Hydraulic Fracturing-Induced Seismicity

34 Any human activity that alters the stress state in the Earth's crust has the potential to induce
35 seismic activity. Induced seismicity has been associated with: mining (e.g., Li et al., 2007);
36 impoundment of reservoirs (e.g., Gupta, 1985); conventional oil and gas extraction (e.g.,
37 Segall, 1989); and subsurface fluid injection, whether for hydraulic fracturing (e.g., Bao and
38 Eaton, 2016), disposal of waste fluids (e.g., Keranen et al., 2013), Carbon Capture and
39 Storage (e.g., Stork et al., 2015), or geothermal energy (e.g., Häring et al., 2008).

40 It has been conclusively demonstrated that injecting fluids into the subsurface can trigger
41 seismicity, where increased pore-fluid pressures lead to the activation of critically-stressed
42 faults (e.g., Raleigh et al., 1976). However, it should be noted that the overwhelming majority
43 of such operations are not thought to cause earthquakes. Nevertheless, as the above practices
44 have increased in scale and become more widespread, the issue of injection-induced
45 seismicity has grown in significance.

46 While much of the recent focus has been on waste-water disposal, several cases of hydraulic
47 fracturing-induced seismicity (HF-IS) have been identified (e.g., B.C. Oil and Gas
48 Commission 2012, 2014; Clarke et al. 2014; Friberg et al., 2014; Darold et al., 2014; Skoumal
49 et al., 2015; Schultz et al. 2015a,b; Atkinson et al., 2016; Bao and Eaton, 2016; Wang et al.,
50 2016). It is vital that our understanding of HF-IS improves, such that industrial operators are
51 capable of mitigating against triggering seismic activity. However, for many of these case
52 examples monitoring arrays were not deployed until after large events had occurred, or
53 available monitoring arrays consisted solely of regional networks, where the nearest station
54 may have been many km from the site. This means that there is often little useful data that can
55 be used to study the processes that happened in the lead-up to these events, and thereby what
56 mitigation steps might have been possible.

The number of cases of HF-IS is very small when compared to the overall number of wells that have been hydraulically stimulated. As such, any mitigation scheme should be capable of quickly differentiating the “normal case”, where hydraulic fracturing does not cause fault re-activation leading to larger events, from the “abnormal case” where large events may be triggered, and therefore where mitigating strategies, such as reducing injection volumes or ceasing injection altogether, may be necessary.

Mitigation of HF-IS

At present, where regulations pertaining to HF-IS have been applied, they have taken the form of Traffic Light Schemes (TLSs), whereby operators take actions based on the magnitude of events induced during operations. These schemes have the advantage of being relatively simple to administer, and can be understood by the public. However, there are somewhat reactive in their nature (as opposed to proactive): an operational response is required, such as reducing or stopping injection, only after an event of a given size has occurred.

The purpose of this paper is not to argue against the use of TLSs, which can play a useful role in the regulation of HF-IS. However, it is our view that, in addition to complying with TLS regulations, operators should seek to mitigate induced seismicity in a more proactive manner. If nothing else, operators will wish to ensure that they remain within the specified TLS thresholds during their operations, since reaching “red lights” entails the imposition of operational constraints, and may also affect operator reputation and confidence with the public.

To take a proactive approach to HF-IS, operators must develop the capacity to model their activities, allowing them to make forecasts about the HF-IS that may occur as their operations continue. In the broadest sense, two types of modelling approach are available: physical and statistical. Physical models aim to simulate the processes that occur during hydraulic stimulation, usually using numerical methods such as finite elements (e.g. Maxwell et al., 2015), discrete elements (e.g., Yoon et al., 2014), rate and state approaches based on

modelled stress changes (e.g., Hakimhashemi et al., 2014), or by resolving modelled stress changes onto pre-existing fault/fracture networks (e.g., Verdon et al., 2015). However, such models often require extensive site characterisation to identify and characterise both nearby faults and the local stress state. Such models also come with a significant number of free parameters that must be “tuned” to provide a reasonable representation of reality. As such they are better suited for understanding the physical processes that have occurred at a site *a posteriori*. For hydraulic fracturing operators who might be required to manage induced seismicity in real time at a significant number of active well sites, simple models with a relatively small number of free parameters are required. In this respect, statistical models become more favourable.

Statistical approaches seek to characterise the observed seismic event population via a statistical model, usually the Gutenberg and Richter (1944) (G-R hereafter) distribution. Such a model can then be extrapolated to estimate the event population that is expected to have occurred by the end of the injection period. Several such models have been proposed, for example: Shapiro et al. (2010); McGarr (2014); Hallo et al. (2014); and van der Elst et al. (2016).

These models are similar in their underlying assumptions: event magnitudes can be characterised by the G-R distribution, and the rate of seismicity is linked in some way to the injection volume. This relationship is then extrapolated based on recorded seismicity during the early stages of injection to estimate what the resulting event population would be once the total volume has been injected. From this estimated population, the largest event size can be forecast. These models have the advantage that they require only a few parameters, which can be measured as operations progress. This makes them better-suited for the task of providing *a priori* mitigation of induced seismicity.

While these models have been tested at several sites (e.g. Hallo et al., 2014; Hajati et al., 2015), the crucial aspect investigated in this paper is that we seek to apply these methods in a prospective manner (e.g. Langenbruch and Zoback, 2016). We do not apply these models

using the overall event population that has been acquired during hydraulic stimulation in a *post hoc* manner. Instead, we put ourselves into the shoes of an operator or regulator, where forecasts must be made using only the data that has been acquired prior to a given point in time. Evidently, the underlying assumption for these methods is that the parameters used to characterise the seismicity as a function of injection volume remain unchanged during a given operation.

We apply these methods to two datasets collected during hydraulic stimulation in the Horn River Shale. These multi-well, multi-stage sites were monitored using downhole microseismic arrays, producing very high quality datasets. These datasets are described in the following section, after which we describe the methods of Shapiro et al. (2010) and Hallo et al. (2014) in greater detail, and apply them to the datasets.

DATASETS

In our case example we examine microseismic datasets from two multi-well, multi-stage hydraulic fracturing treatments conducted in the Horn River Shale formation in British Columbia, Canada. The pads from which the two sets of wells were drilled are approximately 7km apart from each other. In the following we refer to the two datasets as HR1, which was completed in 2011, and HR2, which was completed in 2013. These datasets were provided by the operating company: they are proprietary and cannot be released to the public.

HR1 Microseismic Data

A total of 9 horizontal wells were drilled from the HR1 pad. A total of 146 stages were stimulated, with between 15 – 18 stages per well. Microseismic data was recorded by arrays of up to 100 3-component geophones placed in boreholes adjacent to those being stimulated (in both the vertical and horizontal sections of the wells). The positions of the geophones were varied as stimulation progressed along the wells, in at least 21 configurations.

Data were provided from 76 of the stages, consisting of a total of 140,100 events. These were the stages closest to the heels of the wells, and therefore closest to the monitoring arrays, where the best quality microseismic data could be gathered. Events were located by inverting picked P- and S-wave arrival times through a layered, anisotropic velocity model. A map and cross-section of the HR1 microseismic events are shown in Figure 1. Event magnitudes were calculated by fitting an idealised source model to the event displacement spectra to determine the seismic moment (e.g., Stork et al., 2014). Throughout this paper, when referring to “magnitude” our implication is moment magnitude, M_W . In both cases this processing of the data was performed by a service provider, ESG Solutions.

HR2 Microseismic Data

A total of 10 wells were drilled from the HR2 pad. 237 stages were stimulated, with between 23 – 24 stages per well. Microseismic data was recorded by an array of 96 3-component geophones placed in 3 adjacent boreholes. Data was provided from 119 stages, consisting of 92,700 events. As with the HR1 pad, data was provided for the stages nearest to the heels of the wells, where they are in closest proximity to the monitoring array (and therefore are expected to provide the best quality data). A map and cross-section of the HR2 events are shown in Figure 2.

In both case studies, examination of event locations reveals evidence for the interaction between hydraulic fracturing and faults in the form of planar features extending downwards into the underlying Keg River limestone formation. At HR1, the largest event has a magnitude of $M_W = 1.3$, while at HR2 the largest event has a magnitude of $M_W = 0.5$. In both cases, these magnitudes are larger than what is typically observed when hydraulic fractures propagate through shale gas reservoirs, where magnitudes are generally less than 0 (e.g., Maxwell et al., 2010).

USING EVENT POPULATION STATISTICS TO FORECAST THE LARGEST EVENT SIZE

161 In the following sections, we refer to M_{MAX}^O as the largest magnitude event *observed* during a
 162 particular stage, and M_{MAX}^M as the expected largest magnitude as estimated by a *modelling*
 163 strategy. Ideally, modelling strategies should aim to produce conservative estimates of M_{MAX}^M ,
 164 such that $M_{MAX}^O \leq M_{MAX}^M$. Here we examine the abilities of two published methods, Shapiro
 165 et al. (2010) and Hallo et al. (2014), to forecast M_{MAX}^M during hydraulic stimulation.

166 **Seismogenic Index, Shapiro et al. (2010)**

167 Shapiro et al. (2010) define the Seismogenic Index, S_I as

$$168 \quad S_I = \log_{10}\left(\frac{N_t(M)}{V_t}\right) + bM, \quad (1)$$

169 where $N_t(M)$ is the number of events that have occurred at time t that are larger than a given
 170 magnitude M , b is the G-R b -value for the observed event magnitude distribution (EMD), and
 171 V_t is the cumulative volume injected up until this time (note that Shapiro et al. (2010) use Σ to
 172 denote the seismogenic index: we use S_I instead to differentiate with other uses of Σ
 173 elsewhere in this paper). Assuming that the number of events induced per unit volume
 174 injected does not change, then S_I will be constant: constant S_I has been observed by Dinske
 175 and Shapiro (2013) and van der Elst et al. (2016) for a wide range of cases studies. Shapiro et
 176 al. (2010) show that, in such an instance, if the occurrence of individual events can be treated
 177 as an independent Poisson process, then the probability that an event larger than M does not
 178 occur if a total volume V_T is injected can be calculated as

$$179 \quad \mathbb{P} = \exp(-V_T \cdot 10^{S_I - bM}). \quad (2)$$

180 Re-arranging this equation, we arrive at a forecast for the size of event that will not be
 181 exceeded, given a confidence level χ :

$$182 \quad M_{MAX}^M = \left(S_I - \log\left(\frac{-\ln(\chi)}{V_T}\right) \right) / b. \quad (3)$$

183 In order to provide a mitigation strategy, we are interested in establishing an upper bound for
 184 M_{MAX} , i.e., to establish what size of earthquake will not occur (or is unlikely to occur).

Therefore, for the entirety of this study we consider the upper bound of the distribution described by Shapiro et al. (2010), setting $\chi = 0.95$.

Seismic Efficiency, Hallo et al. (2014)

McGarr (2014) proposed that the cumulative seismic moment released during injection, ΣM_O , is determined by the total cumulative volume of fluid injected:

$$\Sigma M_O = 2\mu V_T, \quad (4)$$

where μ is the rock shear modulus. However, this equation can be considered as a worst-case scenario, where all the strain induced by a volume change is released as seismic energy. In reality, much of the deformation induced by injection will be released aseismically. Hallo et al. (2014) therefore define a seismic efficiency ratio, S_{EFF} , which describes the ratio of observed cumulative moment release to the theoretical maximum given by μV_T . Equation 3 is thereby modified to:

$$\Sigma M_O = S_{EFF} \mu V_T, \quad (5)$$

where S_{EFF} can be estimated at a given time from the cumulative moment release and the cumulative injected volume up until this time.

For a given cumulative seismic moment release, size of the largest event will be determined by the b value. Hallo et al. (2014) show that ΣM_O can be related to the b value, and the largest event detected, M_{MAX}^M , and the minimum magnitude of completeness, M_{MIN} :

$$\Sigma M_O = \frac{b \cdot 10^a \cdot 10^{9.1}}{1.5 - b} \left(10^{(M_{MAX}^M(1.5-b))} - 10^{(M_{MIN}(1.5-b))} \right), \quad (6)$$

where

$$a = b M_{MAX}^M - \log(10^{b\delta} - 10^{-b\delta}), \quad (7)$$

and δ is the probabilistic half-bin size defined around M_{MAX}^M , as described by Hallo et al. (2014). Based on equation 5, we can determine the total expected ΣM_O based on the observed seismic efficiency S_{EFF} and the planned total injection volume V_T . Once we have estimated

209 ΣM_O , we invert equations 6 and 7 to forecast M_{MAX}^M based on the observed b values.
 210 Essentially, M_{MAX}^M is a function of the seismic efficiency, which describes how much seismic
 211 moment is released per unit volume injected, and the b value, which describes whether this
 212 seismic moment is released as a few large events or as many small events.

213 Whereas the Shapiro et al. (2010) S_I method provides a probability distribution for M_{MAX}
 214 (Equation 3), the Hallo et al. (2014) method provides a single estimate for M_{MAX}^M based on
 215 the observed (or forecast) b and S_{EFF} values. As such, assuming the Hallo et al. method is a
 216 true representation of the induced seismicity, random variability alone would mean that the
 217 actual M_{MAX}^O value would be larger than the model for half the cases. As described above, our
 218 aim is to establish conservative M_{MAX}^M values, whereby we have confidence that no events
 219 larger than M_{MAX}^M will occur. Therefore we require a value based on equations 6 and 7 that
 220 also takes into account uncertainties inherent in the approach.

221 To do this we consider synthetic, stochastically generated event populations. By randomly
 222 sampling from a G-R distribution, we generate event populations with a given b value and
 223 ΣM_O chosen randomly from $0.8 < b < 3.5$ and $9 < \log_{10} \Sigma M_O < 14$. We then compare the
 224 largest sampled event (which we refer to as the “synthetic M_{MAX}^O ”) with that forecast from the
 225 given b and ΣM_O values using equations 6 and 7 (the “forecast M_{MAX}^M ”). Our results for 1,000
 226 such realisations are shown in Figure 3. We find that for 98% of model realisations, the
 227 forecast value of M_{MAX}^M is within 0.5 magnitude units of the synthetic M_{MAX}^O . Because we are
 228 primarily concerned with setting a conservative envelope that is not exceeded, in the
 229 following sections we take as M_{MAX}^M the value computed using the Hallo et al. method
 230 (equations 6 and 7) + 0.5.

231 There is currently some debate as to whether there really is a link between injection volume
 232 and the rate and/or size of induced earthquakes (e.g. Atkinson et al., 2016; van der Elst et al.,
 233 2016). This debate stems from fundamental questions as to the nature of rupture mechanics
 234 during induced seismicity. Gischig (2015) describes two end-members for rupture behaviour.
 235 In the first case rupture may initiate within the zone of increased pressure, but uncontrolled

rupture can continue along faults outside of this zone, releasing tectonically-accumulated strain energy. Event size will be therefore determined by tectonic factors such as fault dimensions and *in situ* stress conditions. In the second case the rupture is spatially limited to the zone of increased pore pressure, in which case the injection volume places an *a priori*, deterministic limit on the maximum event size.

The second case, where the injection volume places a deterministic limit on event size, is often characterised by the McGarr (2014) limit (Equation 4). However, observations of events that appear to breach this limit (e.g., Atkinson et al., 2016) indicate that, at least in certain cases, the first of the Gischig (2015) end-members applies. Therefore an *a priori* deterministic limit on event size cannot be assumed based on injection volume.

However, in our approach there is no requirement that $S_{EFF} \leq 1$, and therefore there is no *a priori* deterministic limit to event size. If $S_{EFF} > 1$, this indicates that the cumulative moment released is larger than the strain energy introduced by injection, and therefore that tectonically accumulated strain energy is also being released. Equation (5) requires simply that there is proportionality between V_T and ΣM_O , where S_{EFF} is to be determined by observation for a given site. Van der Elst (2016) examined a range of case studies to investigate whether the number of earthquakes induced during injection is proportional to injection volume, and found strong evidence that this was indeed the case, with the implication that the event nucleation rate is controlled by the injection volume. If b values are constant, then this implies that the cumulative moment release will also be proportional to injection volume.

Application to microseismic data

To compute b values we use the maximum likelihood approach described by Aki (1965). To estimate M_{MIN} , we follow the method described by Clauset et al. (2009) to assess the quality of fit between the observed EMD and the G-R relationship using a Kolmogorov-Smirnov test, choosing as M_{MIN} the smallest magnitude at which the null hypothesis (that the observed distribution can be modelled by the G-R relationship) is not rejected at a 10% significance

level. Fitting a G-R relationship to an observed EMD can be unreliable for low event numbers. Therefore we require a minimum of 50 events with magnitudes larger than M_{MIN} for a reliable measurement. This means that our approach will only provide an estimate for M_{MAX}^M once sufficient microseismic events have occurred.

Figure 4 shows an example of how we apply these methods to the microseismic datasets. Plots for every stage are available in the supplementary materials. We proceed at intervals of 120 seconds. After each interval has elapsed, we re-calculate the b , S_{EFF} , and S_I parameters based on the total volume injected and the events recorded up until this time. We then use equations 3, 6 and 7 to estimate, using the Shapiro et al. (2010) and Hallo et al. (2014) methods, the expected value of M_{MAX}^M given the injection volume that is planned to take place during the next 120s interval.

In the lower panel of Figure 4, we plot the measured values of b , S_{EFF} , and S_I with time. In the upper panel of Figure 4 we compare the resulting forecasts of M_{MAX}^M with observed event magnitudes. We note that in the example shown in Figure 4, the forecast largest event size stabilizes at a value of approximately $M_{MAX}^M = 0.2$ within 40 minutes of the start of injection. This is slightly larger than the largest observed event, which has a magnitude of $M_{MAX}^O = 0.0$ and occurs 140 minutes after the start of injection.

In the following sections we compare M_{MAX}^O with the value of M_{MAX}^M at the time that the largest event occurred. We also compare M_{MAX}^O with M_{MAX}^M at a time 60 and then 30 minutes before the largest event occurred. We do this to identify the capacity of such methods to provide an opportunity for mitigation by giving an operator sufficient warning to alter (or cease) their stimulation program.

Before considering the results of our method as applied to all stages of both datasets, we note several features from Figure 4. Firstly, we note the similarity between the two curves for S_I and $\log_{10}(S_{EFF})$. This is to be expected given how the two parameters are defined. If M_{MIN} is used as the “ M ” term in equation 3, then the difference $S_I - \log_{10}(S_{EFF})$ will be given by:

$$S_I - \log S_{EFF} = \log(N_t(M_{MIN})/V_t) + bM_{MIN} - \log(\Sigma M_O/\mu V_t). \quad (8)$$

Rearranging this equation, and substituting $\Sigma M_O = N_t \langle M_O \rangle$, where $\langle M_O \rangle$ is the mean moment release per event, we get

$$S_I - \log S_{EFF} = bM_{MIN} - \log(\langle M_O \rangle/\mu). \quad (9)$$

In the case studies presented here, M_{MIN} is typically approximately -1.5, b is typically 2, $\langle M_O \rangle$ is typically of the order 10^7 Nm (equivalent to a magnitude of approximately -1) and we approximate the shear modulus as $\mu = 20 \times 10^9$ Pa. Hence the similarity in values between S_I and $\log_{10}(S_{EFF})$. We also note that the values of M_{MAX}^M computed by the two methods are similar. This gives us confidence that both independent methods are providing similar results.

RESULTS

Before showing the results using the two methods described above, in Figure 5 we compare the observed values for M_{MAX}^O for each stage with the values of M_{MAX}^M forecast using the McGarr (2014) equation $M_{MAX}^M = \mu V_T$. We do this primarily to demonstrate that there does not appear to be any correlation between the observed M_{MAX}^O of each stage and the volume injected at the time of occurrence of each event. We also note that the observed magnitudes are far smaller than those estimated by the McGarr (2014) equation.

In Figure 6 we compare the observed and forecast M_{MAX} values using the Hallo et al. (2014) method. As per Figure 4, we compare the forecast M_{MAX}^M values at the time that the largest event occurred, but also compare the forecast M_{MAX}^M values 30 and 60 minutes before the occurrence of the largest event. In Figure 7 we do the same for the Shapiro et al. (2010) method.

We note several features from these results. Firstly, as required, in general $M_{MAX}^M \geq M_{MAX}^O$ for almost every stage. Not only this, but stages that produced smaller events have smaller values of M_{MAX}^M , *id est* there is clear correlation between M_{MAX}^M and M_{MAX}^O . This is encouraging, as it implies that these methods do have some forecasting power, unlike the results provided by

the McGarr (2014) approach shown in Figure 5. This correlation is present even for the T – 60mins measurements, implying that these methods are capable of identifying stages that may induce larger events a significant period of time before such events occur.

There is only 1 stage, at HR2, where both the Shapiro et al. (2010) and Hallo et al. (2014) methods significantly underestimate M_{MAX}^O . We note that this stage had only 131 events in total, making it one of the smallest stages in terms of the number of events. The robustness of statistical techniques such as these will be dependent on the number of events sampled, so it is perhaps unsurprising that stages with fewer events might produce less reliable results.

DISCUSSION

Do seismicity parameters vary during injection stages?

The models we use to forecast M_{MAX}^M are entirely statistical, and do not incorporate any geological information. The major advantage of these statistical approaches is that they are relatively simple to use (requiring only that the volume injected, and the number and magnitude of seismic events can be measured). The principal assumption that underpins this type of approach is that both b , S_{EFF} and/or S_I will remain consistent throughout the injection period. It is by no means clear that this will always be the case.

These parameters might be affected by a range of factors including: the *in situ* stress conditions; the lithology of the rock through which hydraulic fractures are propagating; and the presence of pre-existing fracture networks and/or faults. Generally speaking, the volume of rock influenced by injection increases as the pressure front moves out from the injection well. Therefore, the pressure pulse induced by injection may begin to act on different layers and/or structures as injection continues. It is easy to imagine scenarios where a growing hydraulic fracture intersects with a pre-existing fault, or propagates into an under- or overlying layer that is more seismogenic, resulting in a change in the rate of seismicity and/or b value.

The key question then becomes whether such changes are rapid, or whether there will be a more gradual evolution. If the seismicity changes suddenly then larger events may occur that cannot be anticipated based on the preceding microseismicity. It would therefore be very difficult for an operator to mitigate induced seismicity, as larger events would occur “out of the blue”. In contrast, if such changes occur relatively gradually then an operator may be able to identify an increase in the seismicity rate, or a decrease in the G-R b -value, that would indicate an increasing probability of a larger event occurring. If closely monitored, this might allow an operator to take appropriate mitigating action (reducing pumping rates and/or pressures, or indeed ceasing to pump altogether).

Incidentally, this assumption is also implicit in existing schemes that are used to mitigate induced seismicity, such as TLSs, although this assumption is rarely stated explicitly. If large events are triggered immediately when a HF intersects a fault, then TLSs will be ineffective, because an event that is much larger than the red-light threshold could occur without any prior TLS-based mitigation actions having been taken. In contrast, if there is a more gradual build-up of seismicity upon intersection between a hydraulic fracture and a fault, then the amber and red lights will progressively be triggered, and the appropriate mitigation steps taken.

We note that both Dinske and Shapiro (2013) and van der Elst et al. (2016) have observed remarkably constant values of S_f during fluid injection, across a wide variety of settings including hydraulic fracturing, stimulation of geothermal reservoirs, and during wastewater disposal. There are also sound physical reasons to expect a gradual increase in seismic magnitudes as a hydraulic fracture impinges on a fault, as opposed to a sudden “jump”. When a fracture first meets a fault, both the area of the fault affected, and the volume of fluid injected into the fault will be small. As such, we might expect the initial events to be smaller. As injection continues, the area of the fault affected will increase, as will the volume of fluid injected into it, which would be expected to increase the event magnitudes as injection continues.

This assumption is borne out in the results we present here, most notably in the fact that the forecast M_{MAX}^M values tend to anticipate the observed largest events by at least 60 minutes (Figures 6 and 7). It is also apparent when the evolution of these parameters is examined in detail during each stimulation stage (see supplementary material). The implication is that large induced events do not occur “out of the blue”, but are accompanied by a build-up in seismicity as the stimulation impinges on a pre-existing fault.

Strategy for Mitigation of Induced Seismicity

Based on the above results, we suggest the following strategy for the mitigation of induced seismicity. Prior to the start of operations, an acceptable threshold for M_{MAX}^M is set, based on the vulnerability of nearby populations, buildings and infrastructure to seismic activity, and the expected ground motion that would be caused by events of a given size.

In this case, we arbitrarily set our thresholds as $M_{MAX}^M > 1$. Given the relative lack of buildings, local populations or infrastructure near to this site, this is a relatively conservative threshold, but nevertheless affords a clear demonstration of the approach. Because the results for the Hallo et al. (2014) method show a tighter correlation between M_{MAX}^M and M_{MAX}^O (c.f. Figures 6 and 7), we use this approach as our preferred method to compute M_{MAX}^M . If M_{MAX}^M exceeds this threshold during a stage, then mitigating actions should be taken. In this case we suggest that the mitigating action would be to cease injection and move on to the next stage.

Based on our results, we divide the stages into 3 categories: stages where the $M_{MAX}^M > 1$ threshold is never reached and therefore no mitigation action is indicated (Figure 8a,b); stages where the $M_{MAX}^M > 1$ threshold is reached only after the occurrence of the largest observed event (Figure 8c,d); and stages where the $M_{MAX}^M > 1$ threshold is reached before the occurrence of the largest event (Figure 8e,f).

The first category of stages, where the $M_{MAX}^M > 1$ threshold was not exceeded at any time, is represented in Figure 8a. An example of such a stage is shown in Figure 8b. 159 out of 195 total stages (82%) fall into this category. The circles in Figure 8a show the largest event to

391 occur in each of these stages: the largest event to occur in a stage where the $M_{MAX}^M > 1$
392 threshold was not reached had a magnitude of $M_W = 0.4$.

393 The second category of stages is where the $M_{MAX}^M > 1$ threshold was exceeded, but only after
394 the occurrence of the largest event (Figure 8c). An example of such a stage is shown in Figure
395 8d: in this stage the largest event, which has a magnitude of $M_{MAX}^O = 0.58$, occurs after
396 approximately 1 hour. The $M_{MAX}^M > 1$ threshold is reached after 2 hours of injection. Because
397 the threshold is reached after the occurrence of the largest event, any mitigation steps that
398 might have been taken would not affect the size of largest event to occur during these stages.
399 A total of 16 stages (8%) fall into this category, and M_{MAX}^O for each of these stages is
400 depicted in Figure 8c. The largest magnitude event to occur during these stages had a
401 magnitude of $M_W = 0.88$.

402 The third category of stages is where the $M_{MAX}^M > 1$ threshold was exceeded prior to the
403 occurrence of the largest event. An example of such a stage is shown in Figure 8f: in this
404 stage the $M_{MAX}^M > 1$ threshold is reached after approximately 1 hour of injection. This is over
405 2.5 hours before the occurrence of the largest event, which had a magnitude of $M_{MAX}^O = 1.24$.
406 In other words, the potential for an $M_W > 1$ event is identifiable at a relatively early point
407 during the stage, and it is therefore possible that actions could have been taken that might
408 have mitigated the occurrence of this event. A total of 20 stages (10%) fall into this third
409 category, where the $M_{MAX}^M > 1$ threshold was reached prior to the occurrence of the largest
410 event. These stages are depicted in Figure 8e, where the squares indicate the size of the
411 largest event to occur prior to reaching the $M_{MAX}^M > 1$ threshold, while triangles indicate the
412 eventual largest event to occur. Within this category of stages, three had events with
413 magnitudes larger than $M_W = 1$. However, the largest event to occur before reaching the
414 $M_{MAX}^M > 1$ threshold had a magnitude of $M_W = 0.65$.

415 Overall, we note that for all the stages where the largest event was smaller than $M_{MAX}^O < 0$, no
416 mitigation actions were indicated. For some stages where $0 < M_W < 1$ mitigation actions were
417 indicated, while in others they were not. For all the stages where the largest event exceeded

$M_{MAX}^O > 1$, mitigation actions were always indicated prior to the occurrence of these events. The result is that, for our “mitigated” population there are no stages where the largest event exceeds $M_W > 1$.

Mitigating actions and post-injection seismicity

The major caveat that applied to the results described above is the assumption that ceasing injection can prevent the subsequent larger events from happening. In reality injection was not stopped, and so we cannot know whether cessation of injection during a stage would actually have mitigated the larger events that occurred later in the stage. In other cases of induced seismicity, events have continued with increasing magnitudes even after injection had ceased (e.g., Häring et al., 2008). It is certainly possible that this would have been the case at this site. Therefore it is not possible to definitively conclude that, even if mitigation steps had been taken, further seismicity would not have occurred. Nevertheless, we believe that it is important that operators develop scientific criteria to guide operational decisions with respect to mitigating induced seismicity, and that the results presented here clearly indicate that the methods described in this paper do provide such a basis.

CONCLUSIONS

We have presented case studies from two sites where microseismic monitoring has imaged pre-existing faults being activated during hydraulic fracturing. We investigate the use of two statistical methods found in the literature (Shapiro et al., 2010; Hallo et al., 2014) to forecast the largest event size that might be expected during a hydraulic fracturing stage. The basis of these two methods is to characterise the rate of seismicity with respect to the injection volume, and thereby extrapolate to an expected event distribution once the planned total volume has been injected.

Rather than examining these case studies *post hoc*, we explore the potential of these methods to work in a prospective manner: at each given time-step we only make use of information

that is available prior to this time. We do this to put ourselves in the shoes of an operator or regulator, where decisions must be taken in real time as injection proceeds. We find that the proposed methods can forecast the largest event magnitudes with a reasonable degree of accuracy. This enables us to propose a strategy to mitigate HF-IS, whereby alterations to the injection strategy should be made if M_{MAX}^M exceeds a given threshold. We show that this strategy may have been able to mitigate the larger events that occurred at our case study sites.

The underlying assumption for these methods is that the rate of seismicity with respect to the injection volume will not alter during injection, or that if a fault is encountered, it will evolve gradually, allowing mitigation actions to be taken if real-time monitoring is used. We find that this assumption appears to hold for the datasets considered here. However, further study is required to examine whether this is the case more generally. This highlights the need for good quality seismic monitoring if the science around injection-induced seismicity is to advance. In many of the most well-known case examples, local monitoring arrays were only installed after the largest events had occurred. It is therefore difficult to determine with any certainty what happened in the time leading up to the triggering, and whether an operator could have made observations that in turn might have allowed them to take mitigating actions.

The most effective types of monitoring system are either downhole arrays (e.g., Maxwell et al., 2010), as per both case studies in this paper, or Very Large, Very Dense (VLVD) surface arrays, over which data are migrated and stacked (e.g., Chambers et al., 2010). Unfortunately, the costs of these types of deployment are high, and it is unlikely that such systems will be deployed at every injection project. However, novel processing methods using smaller arrays of seismometers placed at the surface (e.g., Skoumal et al., 2015; Verdon et al., 2017) are being used to improve the quality of datasets available.

Injection induced seismicity is a growing concern for various industries, and regulators are increasingly requiring operators to deploy monitoring arrays, usually to meet a traffic light scheme requirement of some form. We anticipate that, as more case studies become available,

our understanding of injection induced seismicity will grow, and our ability to mitigate such events will thereby improve.

Data and Resources

The datasets presented in this paper were acquired by the operating company, and are proprietary. Therefore they cannot be released to the public.

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References

- Aki, K., 1965, Maximum likelihood estimate of b in the formula $\log N = a - bM$ and its confidence limits: Bulletin of the Earthquake Research Institute, University of Tokyo 43, 237-239.
- Atkinson G.M., Ghofrani H., Assatourians K., 2015. Impact of Induced Seismicity on the Evaluation of Seismic Hazard: Some Preliminary Considerations: Seismological Research Letters 86, 1009-1021.
- Atkinson G.M., Eaton D.W., Ghofrani H., Walker D., Cheadle B., Schultz R., Shcherbakov R., Tiampo K., Gu J., Harrington R.M., Liu Y., van der Baan M., Kao H., 2016. Hydraulic fracturing and seismicity in the Western Canada Sedimentary Basin: Seismological Research Letters 87, 1-17.
- Bao X., and Eaton D.W., 2016. Fault activation by hydraulic fracturing in western Canada: Science, *in press*. DOI: 10.1126/science.aag2583

495 B.C. Oil and Gas Commission, 2012. Investigation of Observed Seismicity in the Horn River
 496 Basin. Accessed from <http://www.bcogc.ca/node/8046/download> on 23.7.2015.

497 B.C. Oil and Gas Commission, 2014. Investigation of Observed Seismicity in the Montney
 498 Trend. Accessed from <https://www.bcogc.ca/node/12291/download> on 23.7.2015.

499 Chambers K., Kendall J-M., Brandsberg-Dahl S., Rueda J., 2010. Testing the ability of
 500 surface arrays to monitor microseismic activity: Geophysical Prospecting 58, 821-830.

501 Clarke H., Eisner L., Styles P., Turner P., 2014. Felt seismicity associated with shale gas
 502 hydraulic fracturing: The first documented example in Europe: Geophysical Research
 503 Letters 41, 8308-8314.

504 Clauset A., Shalizi C.R., Newman M.E.J., 2009. Power-law distributions in empirical data:
 505 Society for Industrial and Applied Mathematics Review 51, 661-703.

506 Darold A., Holland A.A., Chen C., Youngblood A., 2014. Preliminary analysis of seismicity
 507 near Eagleton 1-29, Carter County, July 2014: Oklahoma Geological Society Open File
 508 Report, OF2-2014.

509 Dinske C. and Shapiro S.A., 2013. Seismotectonic state of reservoirs inferred from magnitude
 510 distributions of fluid-induced seismicity: Journal of Seismology 17, 13-25.

511 Friberg P.A., Besana-Ostman G.M., Dricker I., 2014. Characterisation of an earthquake
 512 sequence triggered by hydraulic fracturing in Harrison County, Ohio: Seismological
 513 Research Letters 85, 1295-1307.

514 Gischig V.S., 2015. Rupture propagation behavior and the largest possible earthquake
 515 induced by fluid injection into deep reservoirs: Geophysical Research Letters 42, 7420-
 516 7428.

517 Gupta H.K., 1985. The present status of reservoir induced seismicity investigations with
 518 special emphasis on Koyna earthquakes: Tectonophysics 118, 257-279.

519 Gutenberg B. and Richter C.F., 1944. Frequency of earthquakes in California: Bulletin of the
 520 Seismological Society of America 34, 185-188.

521 Hajati T., Langenbruch C., Shapiro S.A., 2015. A statistical model for seismic hazard
522 assessment of hydraulic-fracturing-induced seismicity: *Geophysical Research Letters* 42,
523 10601-10606.

524 Hakimhashemi A.H., Schoenball M., Heidbach O., Zang A., Grünthal G., 2014. Forward
525 modelling of seismicity rate changes in georeservoirs with a hybrid geomechanical-
526 statistical prototype model: *Geothermics* 52, 185-194.

527 Hallo M., Oprsäl I., Eisner L., Ali M.Y., 2014. Prediction of magnitude of the largest
528 potentially induced seismic event: *Journal of Seismology* 18, 421-431.

529 Häring M.O., Schanz U., Ladner F., Dyer B.C., 2008. Characterisation of the Basel 1
530 enhanced geothermal system: *Geothermics* 37, 469-495.

531 Keranen K.M., Savage H.M., Abers G.A., Cochran E.S., 2013. Potentially induced
532 earthquakes in Oklahoma, USA: Links between wastewater injection and the 2011 M_w 5.7
533 earthquake sequence: *Geology* 41, 699-702.

534 Langenbruch C. and Zoback M.D., 2016. How will induced seismicity in Oklahoma respond
535 to decreased saltwater injection rates? *Science Advances* 2, e1601542,

536 Li T., Cai M.F., Cai M., 2007. A review of mining-induced seismicity in China: *International*
537 *Journal of Rock Mechanics and Mining Sciences* 44, 1149-1171.

538 Maxwell S.C., Rutledge J., Jones R., Fehler M., 2010. Petroleum reservoir characterization
539 using downhole microseismic monitoring: *Geophysics* 75, A129-A137.

540 Maxwell S.C., Zhang F., Damjanac B., 2015. Geomechanical modeling of induced seismicity
541 resulting from hydraulic fracturing: *The Leading Edge* 34, 678-683

542 McGarr A., 2014. Maximum magnitude earthquakes induced by fluid injection: *Journal of*
543 *Geophysical Research* 119, 1008-1019.

544 Raleigh C.B., Healy J.H., Bredehoeft J.D., 1976. An experiment in earthquake control at
545 Rangely, Colorado: *Science* 191, 1230-1237.

- Schultz R., Stern V., Novakovic M., Atkinson G., Gu Y.J., 2015a. Hydraulic fracturing and the Crooked Lake sequences: Insights gleaned from regional seismic networks: *Geophysical Research Letters* 42, 2750-2758.
- Schultz R., Mei S., Pana D., Stern V., Gu Y.J., Kim A., Eaton D., 2015b. The Cardston earthquake swarm and hydraulic fracturing of the Exshaw Formation (Alberta Bakken play): *Bulletin of the Seismological Society of America* 105, 2871-2884.
- Segall P., 1989. Earthquakes triggered by fluid extraction: *Geology* 17, 942-946.
- Shapiro S.A., Dinske C., Langenbruch C., 2010. Seismogenic index and magnitude probability of earthquakes induced during reservoir fluid stimulations: *The Leading Edge* 29, 304-309.
- Skoumal R.J., Brudzinski M.R., Currie B.S., 2015. Induced earthquakes during hydraulic fracturing in Poland Township, Ohio: *Bulletin of the Seismological Society of America* 105, 189-197.
- Stork A.L., Verdon J.P., Kendall J-M. 2014. Assessing the effect of microseismic processing methods on seismic moment and magnitude calculations: *Geophysical Prospecting* 62, 862-878.
- Stork A.L., Verdon J.P., Kendall J-M., 2015. The microseismic response at the In Salah carbon capture and storage (CCS) site: *International Journal of Greenhouse Gas Control* 32, 159-171.
- van der Elst, N.J., Page M.T., Weiser D.A., Goebel T.H.W., Hosseini S.M., 2016. Induced earthquake magnitudes are as large as (statistically) expected: *Journal of Geophysical Research* 121, 4575-4590.
- Verdon J.P., Stork A.L., Bissell R.C., Bond C.E., Werner M.J., 2015. Simulation of seismic events induced by CO₂ injection at In Salah, Algeria: *Earth and Planetary Science Letters* 426, 118-129.

Verdon J.P., Kendall J-M., Hicks S.P., Hill P., 2017. Using beam-forming to maximise the detection capability of broadband seismometer arrays deployed to monitor oilfield activities: Geophysical Prospecting, *in press*.

Yoon J.S., Zang A., Stephansson O., 2014. Numerical investigation on optimized stimulation of intact and naturally fractured deep geothermal reservoirs using hydro-mechanical coupled discrete particles joints model: Geothermics 52, 165-184.

Wang R., Gu Y.J., Schultz R., Kim A., Atkinson G., 2016. Source analysis of a potential hydraulic-fracturing-induced earthquake near Fox Creek, Alberta: Geophysical Research Letters 43, 564-573.

(a)

(b)

592 Figure 1: Map (a) and cross-section (b) views of microseismic events recorded during hydraulic
 593 fracturing at HR1. Events are coloured by the number of the stage with which they are associated. The
 594 black lines mark the horizontal wells.

(a)

598

(b)

599 *Figure 2: Map (a) and cross-section (b) views of microseismic events recorded during hydraulic*
 600 *fracturing at HR2. Events are coloured by the number of the stage with which they are associated. The*
 601 *black lines mark the tracks of the horizontal wells.*

602

603 *Figure 3: Numerical evaluation of the uncertainties inherent when using equations 6 and 7 to forecast*
 604 *M_{MAX} . A modelled population of events is sampled from a G-R distribution. M_{MAX} is forecast, and*
 605 *compared with the largest event in the simulated population. In (a) we compare the synthetic and*
 606 *forecast values, while in (b) we show a histogram of the differences between the forecast and modelled*
 607 *values.*

608

Figure 4: Example demonstrating how we forecast M_{MAX}^M during a HF stage. In the lower panel we update b , S_{EFF} and S_I during injection. Based on these parameters, we estimate M_{MAX}^M using the methods described by Shapiro et al. (2010) and Hallo et al. (2014), and compare these to the observed event population. The vertical dashed lines in the upper panel represent the M_{MAX}^M estimates at the time of the largest event, and 30 and 60 minutes prior to this event. This data is from stage HR1-A-S10.

Figure 5: Comparison between the observed M_{MAX}^O for every stage of both datasets, and that estimated using the McGarr (2014) equation, where M_{MAX}^M is directly determined by the injected volume. Symbols are coloured by $\log_{10}(N)$, where N is the total number of events per stage. The dashed line indicated a 1:1 ratio.

Figure 6: Comparison between the observed M_{MAX}^O for every stage of both datasets, and that estimated using the Hallo et al. (2014) approach. The upper panels show crossplots of observed and modelled M_{MAX}^M values, while the lower panels show histograms of $M_{MAX}^M - M_{MAX}^O$. For each case we show the values of M_{MAX}^M at the time that the largest event occurred, and at 30 and 60 minutes prior to this time. The symbols are coloured by $\log_{10}(N)$, where N is the total number of events per stage. The dashed lines in the upper panels represent $M_{MAX}^O = M_{MAX}^M$. Note that for a handful of stages, robust estimates are only obtained within 30 or 60 minutes of the largest event. In such cases, no M_{MAX}^M value is returned at the $T - 30$ or $T - 60$ cases, and so there are slightly fewer points plotted for these cases.

Figure 7: Comparison between the observed M_{MAX}^O for every stage of both datasets, and that estimated using the Shapiro et al. (2010) approach. This figure follows the same format as Figure 6.

(c)

(d)

(e)

(f)

Figure 8: Testing the ability of the proposed approach to mitigate induced seismicity. In (a) we show M_{MAX}^O for each stage that did not reach the $M_{MAX}^M > 1$ threshold. An example of such a stage, where no mitigation actions would have been taken, is shown in (b). In (c) we show M_{MAX}^O for each stage that reached the mitigation threshold, but only after the largest event had occurred. In such cases, any mitigation steps would not affect M_{MAX}^O (since the largest event has already occurred). In (d) we show an example of such a stage. In (e) we show M_{MAX}^O for each stage that reached the $M_{MAX}^M > 1$ threshold prior to the occurrence of M_{MAX}^O . The triangles show the values of M_{MAX}^O that actually occurred. The squares show the largest event that had occurred prior to reaching the threshold. In (f) we show an example of such a stage.