



Mancini, S., Werner, M., Segou, M., & Baptie, B. J. (2021). Probabilistic Forecasting of Hydraulic Fracturing Induced Seismicity Using an Injection-Rate Driven ETAS Model. *Seismological Research Letters*, 92(6), 3471-3481. <https://doi.org/10.1785/0220200454>

Peer reviewed version

Link to published version (if available):
[10.1785/0220200454](https://doi.org/10.1785/0220200454)

[Link to publication record in Explore Bristol Research](#)
PDF-document

This is the author accepted manuscript (AAM). The final published version (version of record) is available online via <https://doi.org/10.1785/0220200454> at Seismological Society of America . Please refer to any applicable terms of use of the publisher.

University of Bristol - Explore Bristol Research

General rights

This document is made available in accordance with publisher policies. Please cite only the published version using the reference above. Full terms of use are available: <http://www.bristol.ac.uk/red/research-policy/pure/user-guides/ebr-terms/>

Confidential manuscript submitted to Seismological Research Letters

1 **Probabilistic Forecasting of Hydraulic Fracturing Induced Seismicity**
2 **Using an Injection-Rate Driven ETAS Model**

3
4 **S. Mancini^{1,2}, M. J. Werner², M. Segou¹, and B. Baptie¹**

5 ¹ British Geological Survey, Lyell Centre, EH10 4AP, Edinburgh, UK

6 ² School of Earth Sciences, University of Bristol, BS8 1RL Bristol, UK

7
8 Corresponding author: Simone Mancini (simone@bgs.ac.uk)

9
10 *Declaration of Competing interests:*

11 The authors acknowledge there are no conflicts of interest recorded.

12
13
14
15
16
17
18
19
20
21
22
23
24
25
26

27 **Abstract**

28 The development of robust forecasts of human-induced seismicity is highly desirable to
29 mitigate the effects of disturbing or damaging earthquakes. We assess the performance of a
30 well-established statistical model, the Epidemic-Type Aftershock Sequence (ETAS) model,
31 with a catalog of ~93,000 microearthquakes observed at the Preston New Road (UK)
32 unconventional shale gas site during and after hydraulic fracturing of the PNR-1z and PNR-2
33 wells. Because ETAS was developed for slower loading rate tectonic seismicity, in order to
34 account for seismicity generated by pressurized fluid we also generate three modified ETAS
35 with background rates proportional to injection rates. We find that (1) the standard ETAS
36 captures low seismicity between and after injections but is outperformed by the modified model
37 during high seismicity periods, and (2) the injection-rate driven ETAS substantially improves
38 when the forecast is calibrated on sleeve-specific pumping data. We finally forecast out-of-
39 sample the PNR-2 seismicity using the average response to injection observed at PNR-1z,
40 achieving better predictive skills than the in-sample standard ETAS. The insights from this
41 study contribute towards producing informative seismicity forecasts for real-time decision
42 making and risk mitigation techniques during unconventional shale gas development.

43

44 **Introduction**

45 Seismicity induced by fluid injections is a growing concern (*Schultz et al.*, 2020) and references
46 therein). Many countries are witnessing an increased development of subsurface geo-energy
47 reservoirs, including unconventional shale gas development, enhanced geothermal energy
48 systems, fluid injection in salt mine fields, wastewater injection, and underground storage of
49 liquid carbon (*Ellsworth*, 2013). These activities promote seismicity in previously low seismic
50 hazard regions or further increase high seismic rates. In recent years, induced seismicity with
51 moderate magnitudes (M5-5.7) in regions such as the central United States, South Korea and

52 southwestern China has led to significant damages and losses (*Keranen et al.*, 2013; *Ellsworth*
53 *et al.*, 2019; *Lee et al.*, 2019; *Lei et al.*, 2020). While several hypotheses about the interplay of
54 deterministic physical mechanisms controlling the seismic response to subsurface fluid
55 injection are currently under investigation (*Atkinson et al.*, 2020), probabilistic methods
56 provide a framework for current epistemic and aleatory uncertainties. Indeed, statistical models
57 of injection-induced seismicity have shown some skill in capturing the complex range of
58 seismic responses to fluid injections (*e.g.*, *Shapiro et al.*, 2007; 2010; *Kiraly-Proag et al.*, 2016;
59 *Verdon and Budge*, 2018). In particular, a popular statistical method, the Epidemic-Type
60 Aftershock Sequence (ETAS) model (*Ogata*, 1988), originally developed to reproduce the
61 short-term clustering of tectonic earthquakes, was tested under different fluid-induced
62 seismicity scenarios including natural circulation of fluids at depth (*Hainzl and Ogata*, 2005)
63 as well as human-related activities, such as natural gas extraction (*Bourne and Oates*, 2017),
64 Enhanced Geothermal Systems (EGS - *e.g.* *Bachmann et al.*, 2011; *Mena et al.*, 2013; *Asanuma*
65 *et al.*, 2014), hydraulic fracturing for unconventional shale gas development (HF - *e.g.* *Lei et*
66 *al.*, 2017; 2019; *Jia et al.*, 2020), and wastewater disposal (*Llenos and Michael*, 2013). These
67 studies concluded that fluid-driven seismicity has distinctive spatiotemporal characteristics,
68 some of which are different from the ‘regular’ tectonic seismicity dominated by earthquake-
69 to-earthquake triggering mechanisms. While the standard ETAS features a stationary
70 background rate due to slower tectonic loadings, *Bachmann et al.* (2011) introduced an ETAS
71 model with a background rate linearly proportional to the injection rate and found that this
72 model performed best in forecasting the seismicity induced in Basel (Switzerland) due to the
73 stimulation of a deep geothermal energy reservoir.

74 In its limited number of applications to HF environments, the ETAS model was mostly used
75 explore the behavior of HF-induced seismicity and to show that time-varying background rates
76 positively correlate with injection operations (*Lei et al.*, 2019; *Jia et al.*, 2020). *Lei et al.* (2017)

77 showed that an ETAS model featuring a non-stationary background rate better reproduces the
78 observed features of seismicity when an external forcing is applied (*e.g.*, fluid flow or aseismic
79 slip in cases of induced and natural seismicity, respectively), but their primary scope was not
80 to assess ETAS performance in a formal forecasting experiment.

81 In this study, we probe the suitability of the ETAS model as a statistical tool for near real-time
82 forecasts of the seismic rates during and after HF operations. We expand on previous
83 applications of the ETAS model to HF by quantitatively assessing the predictive skills of a
84 suite of temporal ETAS models that (1) are calibrated and tested on a much richer
85 microseismicity dataset, (2) seek to reproduce seismic rates from a wider magnitude range
86 (from $M \sim 3$ down to $M = -1.5$), (3) explore how the forecast performance changes under different
87 modelling assumptions (standard vs. modified model formulations) and parameterizations (in-
88 sample vs. out-of-sample forecasts), and (4) test the influence of expressing the non-stationary
89 background rates by using either averaged or sleeve-specific fluid pumping parameters.

90 We take advantage of a rich microseismicity dataset recorded at Preston New Road, Lancashire
91 (UK), during unconventional shale gas development by Cuadrilla Ltd in two wells, PNR-1z in
92 2018 (*Clarke et al.*, 2019) and PNR-2 in 2019. First, we implement the ETAS model in its
93 original tectonic formulation and assess whether (1) it captures the temporal evolution of the
94 microseismicity, and (2) parameters optimized using the available data improve model
95 performance. Second, we implement a modified ETAS model featuring a background
96 seismicity rate proportional to the injection rate following *Bachmann et al.* (2011) but here
97 applied in the context of HF. This presents a particular challenge as HF operations feature short
98 injection episodes along different sleeves, while EGS injections are continuous with gradually
99 changing flow rates at a single injection point. Within the modified ETAS class, we (1) assess
100 model performance against the standard ETAS model, and (2) quantify the influence of using
101 an average (bulk) constant of proportionality between seismicity and injection rates calculated

102 over the entire period of operations at each well versus constants specifically calibrated on
103 individual injection periods. For both ETAS classes we also perform an out-of-sample
104 experiment where we calibrate the ETAS model on PNR-1z data and then use it to
105 independently forecast microseismicity during PNR-2. We rank the forecasts by means of
106 likelihood scores, a well-established metric (*e.g.*, used within the Collaboratory for the Study
107 of Earthquake Predictability, CSEP, *Michael and Werner*, 2018). The comparative
108 performance evaluation illustrates the predictive skills of injection-rate driven ETAS models
109 and how these may inform real-time decision-making by operators and regulators during HF
110 operations.

111

112 **Operations and seismicity at Preston New Road, UK**

113 Hydraulic fracturing operations at the PNR-1z well occurred between 15 October and 17
114 December 2018. The well ran for 700 m horizontally through the natural gas-bearing
115 Carboniferous formation of the Lower Bowland Shale at a depth of ~ 2.3 km (*Clarke et al.*,
116 2018). A total of 17 sleeves were hydraulically fractured (Figure 1a) with mini fracs at 18
117 additional sleeves, consisting of a few tens of m^3 of fluid pumped. Overall, a total of ~ 4600 m^3
118 of slick water fluid was injected (Figure 2a) with an average volume per sleeve of 234 m^3 (and
119 a maximum $V_{\text{MAX}} = 431$ m^3). Hydraulic fracturing was paused between 3 November and 4
120 December 2018 as flow-back from the well took place. The microseismicity at PNR-1z was
121 recorded by a downhole array in the adjacent PNR-2 well consisting of 12 three-component
122 geophones that detected over 38,000 events. Although local 3D reflection seismic surveys
123 acquired before the start of operations revealed the presence of pre-existing seismic
124 discontinuities, these were located far from the well and did not present any clear correlation
125 with the initial microseismicity (*Clarke et al.*, 2019). As injection proceeded, hydraulic
126 fractures started intersecting another pre-existing (but not previously identified) subvertical

127 NE-striking seismogenic feature, located NE of the well. The largest magnitude event that
128 occurred on 11 December 2018 ($M_L = 1.5$) activated a section of such structure. However, as
129 reported by *Kettlety et al.* (2020a), it is not clear whether this was a single contiguous fault or
130 a dense zone of fractures.

131 Here, we use the available earthquake catalog that includes origin times and moment
132 magnitudes (M_w) as determined by Schlumberger Ltd., the geophysical processing contractor.
133 The limited dynamic range of the downhole geophones leads to problems in magnitude
134 estimation for $M_w \geq 0.0$ events due to clipping. To avoid a potential bias, we matched these
135 with events in the catalog obtained from broadband surface stations operated by the British
136 Geological Survey (BGS) that reported 172 events with local magnitudes (M_L). We then
137 replaced the moment magnitudes for all $M_w \geq 0.0$ events in the downhole catalog with the
138 corresponding local magnitude estimate, following *Clarke et al.* (2019) for the same dataset.
139 This ad hoc solution to the problem of PNR-1z magnitude conversions remains the subject of
140 ongoing research (*Baptie et al.*, 2020). *Clarke et al.* (2019) argued that assuming $M_L = M_w$ for
141 all $M_w \geq 0.0$ events does not produce anomalies in the frequency-magnitude distribution,
142 suggesting that this simple approach is reasonable.

143 Figure 2a shows a histogram of the hourly number of events during operations along with the
144 cumulative volume of injected fluid. The observed seismicity at PNR-1z shows multiple peaks
145 that visually correlate well with the pumping periods and then decay rapidly with time after
146 injection stops. We find evidence of considerable variations in seismic responses despite
147 comparable injection rates across sleeves (*e.g.*, Figure 2c-d). For instance, at sleeve #2
148 (injection stage S02) event rates increase as soon as injection starts and remain relatively stable
149 (Figure 2c), while at sleeve #40 (injection stage S17) there is a delayed onset of seismicity
150 followed by substantially higher rates (Figure 2d).

151 The horizontal PNR-2 well runs roughly parallel to PNR-1z offset by approximately 200 m
152 and was drilled through the upper part of the Lower Bowland Shale formation at a depth of
153 ~2.1 km. Operations started on 15 August 2019 but were suspended on 26 August following a
154 $M_L = 2.9$ earthquake that was felt up to a few kilometers from the epicenter (*Cremen and*
155 *Werner, 2020*). Aftershocks of this event illuminated a SE-striking fault, a clearly different
156 feature than the one activated during hydraulic stimulation at PNR-1z. Furthermore, the latter
157 did not show any seismicity during operations at PNR-2; it is likely that a barrier blocking any
158 interaction between the two zones was created by lateral lithological variabilities as well as by
159 the notable vertical and lateral separation between the two wells (*Kettlety et al., 2020b*).

160 PNR-2 seismicity was recorded by a downhole array of 12 geophones in the adjacent PNR-1z
161 well, and the final catalog, extending up to 2 October 2019, consists of over 55,000
162 microseismic events (Figure 1b) with magnitudes reported as M_w . We added a correction of
163 0.15 magnitude units to the downhole moment magnitudes following *Baptie et al. (2020)*.
164 Furthermore, the PNR-2 catalog suffers from brief but critical data gaps that result in a loss of
165 otherwise recorded seismic events, including the largest event in the sequence ($M_L = 2.9$) and
166 presumably its early aftershocks. We filled these gaps with events recorded by the combined
167 surface network of the BGS and the operator (*Baptie and Luckett, 2019*).

168 The early earthquake productivity at PNR-2 appears an order of magnitude larger than that
169 observed during the initial injection stages at PNR-1z, even under similar injected volumes
170 (Figure 2b). The complexity of the seismic response to injection is similar to PNR-1z (Figure
171 2e). As at PNR-1z, we observe a general positive co-dependency between seismicity and fluid
172 injection at PNR-2.

173

174 **Methods**

175 **The standard ETAS model**

176 The Epidemic-Type Aftershock Sequence (ETAS) model (*Ogata, 1988*) is a statistical model
 177 of the time-magnitude characteristics of triggered tectonic seismicity. The model treats
 178 seismicity as a self-exciting stochastic point process, in which each earthquake produces
 179 offspring with magnitudes independently sampled from the Gutenberg-Richter distribution
 180 (that is, parent earthquakes can trigger larger events with some probability). The seismic rate
 181 $\lambda(t)$ at time t is given by a time-independent background rate (μ) plus a function accounting
 182 for the history (H_t) of triggering contributions from all previous events at time t_i and with
 183 magnitude M_i prior to t :

184

$$185 \quad \lambda(t | H_t) = \mu + \sum_{i:t_i < t} K e^{\alpha(M_i - M_{cut})} \cdot c^{p-1} (t - t_i + c)^{-p} (p - 1), \quad (1)$$

186

187 where the sum includes empirically observed relations that (1) describe the short-term
 188 aftershock productivity of events above a minimum triggering threshold (M_{cut}) with
 189 parameters K and α , (2) determine an Omori-Utsu temporal decay of the triggered rate with
 190 exponent p and a constant c (*Utsu, 1961*). We estimate the parameters (μ, K, α, c, p), by
 191 maximizing the log-likelihood function (*Zhuang et al., 2012*) on a seismic catalog with N
 192 events and over a period from T_0 to T_1 :

$$193 \quad \log L(\mu, K, \alpha, c, p) = \sum_{i=1}^N \log \lambda(t_i | H_t) - \int_{T_0}^{T_1} \lambda(t) dt. \quad (2)$$

194 Forecasts of the ETAS model require simulations because the rate is conditional on the history
 195 (e.g., *Zhuang and Touati, 2015; Seif et al., 2017*).

196 We create three versions of the standard ETAS model (the ‘‘ETAS1’’ class). In *ETAS1-*
 197 *optimized* we estimate ETAS parameters from the target catalog (either PNR-1z or PNR-2) and
 198 thus perform an in-sample (best-case) forecast evaluation. In *ETAS1-unoptimized* we use the

199 parameters estimated from PNR-1z data to forecast the PNR-2 seismicity out-of-sample.
 200 *ETAS1-global* serves as an alternative benchmark model with the most recently estimated
 201 ETAS parameters from global subduction zones (except for the background rate) by *Zhang et*
 202 *al.* (2020). We select parameters from interplate settings because these might represent the
 203 tectonic counterpart that most closely matches the forcing and boundary conditions of in-situ
 204 fluid-induced seismicity environments, that is, high stressing rates and relatively short-lived
 205 aftershock sequences.

206

207 **The modified ETAS model for injection-induced seismicity**

208 In the second forecast class (“ETAS2”), we modify the ETAS model to account for events
 209 forced by an external driver. We couple the background rate to the time-dependent fluid
 210 injection rate $I_r(t)$:

$$211 \quad \lambda_m(t | H_t) = \mu(I_r) + \sum_{i:t_i < t} K e^{\alpha(M_i - M_{cut})} \cdot c^{p-1} (t - t_i + c)^{-p} (p - 1), \quad (3)$$

212 with λ_m a “modified” seismic rate and the background rate $\mu(I_r)$ now assumed to be linearly
 213 related to the injection rate via a constant of proportionality c_f (*Bachmann et al.*, 2011):

$$214 \quad \mu(I_r) = c_f I_r(t). \quad (4)$$

215 To estimate c_f , we maximize:

$$216 \quad \log L(c_f, K, \alpha, c, p) = \sum_{i=1}^N \log \lambda_m(t_i | H_t) - \int_{T_0}^{T_1} \lambda_m(t) dt. \quad (5)$$

217 Within the ETAS2 class, we develop three forecast versions. In *ETAS2-bulk* we estimate and
 218 use only a single value of c_f for each well, fit over the entire period of operations. *ETAS2-*
 219 *specific* implements specific values of c_f for each sleeve, calibrated within the individual
 220 injection periods; in this model, we fix the triggering parameters (K, c, p, α) to the respective

221 values previously obtained for *ETAS2-bulk* assuming that the contribution of event-to-event
222 interactions does not change in different injection periods, when the external forcing is likely
223 to be the dominant mechanism of earthquake production. Finally, *ETAS2-unoptimized* uses the
224 ETAS parameters estimated on the PNR-1z catalog (including its bulk proportionality
225 constant) to forecast out-of-sample the expected seismic response at PNR-2.

226 Simulating ETAS2 models requires a different method for background events during injection
227 periods. We apply the thinning algorithm (e.g. *Zhuang and Touati, 2015*): (i) estimate a mean
228 expected number of forced events (\overline{N}_f) by multiplying c_f by the injection rate integrated over
229 the duration of either the injection period or the forecast window (whichever is shorter); (ii)
230 draw a random variable (N_f) from a Poisson distribution with mean equal to \overline{N}_f ; (iii) distribute
231 the N_f events in time according to a piece-wise linear, non-homogeneous Poisson process with
232 rate $\mu(I_t)$ driven by the injection rate (smoothed using 1-minute moving windows); (iv)
233 simulate all aftershock generations triggered by the directly forced events by means of the
234 standard procedure.

235

236 For consistency, all six ETAS versions are (1) updated hourly or when an injection period starts
237 (whichever comes sooner), and (2) estimated by 1,000 stochastic ETAS simulations with fixed
238 $M_{\max} = 6.5$ (the most likely regional maximum expected tectonic magnitude; *Woessner et al.*,
239 2015). It is worth noting that incomplete datasets can bias the estimation of the ETAS
240 parameters and potentially lead to seismic rate underpredictions (*Seif et al.*, 2017). For the
241 PNR-1z microseismicity catalog, we estimate a magnitude of completeness (M_c) between -1.2
242 and -1.5 (Figure S1a), while our M_c estimate for PNR-2 is below -1.5 (Figure S1b). However,
243 $M \geq -1.2$ events represent only $\sim 7\%$ of earthquakes recorded at PNR-1z. Furthermore, here we
244 are interested in producing earthquake models that can forecast events also during periods of
245 intense injection-induced seismicity, which instead consist primarily of very small magnitude

246 earthquakes. Therefore, to find a pragmatic compromise and to increase the number of events
 247 to around 20% of the entire PNR-1z dataset, we conduct our analyses using the lower bound
 248 of the estimated PNR-1z catalog completeness range ($M_c = -1.5$). For comparability, we use
 249 the same magnitude threshold for PNR-2. Accordingly, all our ETAS models seek to forecast
 250 the number of $M \geq -1.5$ events at the two wells.

251

252 In the electronic supplement, we report a summary of the tested ETAS versions (Table S1) and
 253 the values of the ETAS parameters (Table S2), including the bulk and sleeve-specific values
 254 of c_f (Tables S3 and S4 for PNR-1z and PNR-2, respectively).

255

256 **Evaluation of model performance**

257 Because each forecast consists of a probability distribution of earthquake numbers over the
 258 forecast period, we evaluate and rank forecast models using a probabilistic score, namely the
 259 log-likelihood values. The score quantifies the likelihood of the observed number if the models
 260 were the data-generator, specifically the logarithm of the probability $Pr(\omega|model)$ of observing
 261 ω earthquakes given the ETAS forecasts (*Zechar, 2010*):

262

$$263 \quad LL(\omega|model) = \log(Pr(\omega|model)). \quad (6)$$

264

265 To compensate for the limited number of simulations, which is likely to under-sample the range
 266 of possible simulated ETAS rates, we approximate the simulation histogram of each forecast
 267 window with a Negative Binomial Distribution (NBD; *Harte, 2015*) (Figures S2 and S3). We
 268 choose the two-parameter NBD because it characterizes earthquake clustering and process
 269 overdispersion much better than the Poisson distribution (*Kagan, 2010*). We calculate the

270 likelihood scores from the fitted NBD. Greater log-likelihood scores indicate greater predictive
271 skill.

272

273 **Results**

274 **Forecast timeseries**

275 In Figures 3a and 4a, we present the incremental hourly timeseries of the three in-sample ETAS
276 forecasts for PNR-1z and PNR-2. We select illustrative subperiods characterized by (1) weak
277 and strong seismic responses to injection, and (2) seismicity without injection. The panels
278 compare the observed number of $M \geq -1.5$ events per hour with the mean and 95% predictive
279 interval of the ETAS model. Firstly, we find that the ETAS1 class projects the onset of
280 increased rates with a 1-hour delay compared to observations. This is not an unexpected effect
281 due to the scarcity of $M \geq -1.5$ parent earthquakes prior to each injection period and the fact
282 that ETAS1 does not account for external seismicity forcing. Secondly, the standard *ETAS1-*
283 *optimized* severely underestimates the observed rates by an order of magnitude during the
284 higher seismicity periods, whether the seismic response to injection is weak or strong. The
285 reason for this underprediction is the fact that ETAS1-optimized lacks information about
286 impending active fluid injections. In contrast, other forecast time windows characterized by
287 underpredictions, such as those immediately following the stop of injections, may suffer from
288 the possible temporary incompleteness of the catalog. Although the estimated ETAS
289 parameters may compensate for this effect, the time-varying incompleteness results in some
290 target periods with fewer small events that would have otherwise increased the chances of
291 triggering additional events. Therefore, the early post-injection model performance might
292 improve with a more complete catalog. However, in post-injection conditions (*i.e.*, a few hours
293 after the end of pumping), when any earthquake clustering is likely driven by event-to-event
294 triggering, *ETAS1-optimized* generally reproduces well the hourly seismicity within the

295 model's 95% ranges at PNR-1z (Figure 3a) and PNR-2 (Figure 4a). Interestingly, during
296 periods of no injection and low seismicity at PNR-1z, the 95% forecast range often
297 encompasses the critical value of zero events, reflecting the intrinsic stochasticity of the ETAS
298 model.

299 The ETAS2 class, featuring an injection-rate-driven background rate, substantially reduces the
300 discrepancies with the observed rates. *ETAS2-bulk*, which captures the average seismic
301 response to injection, both under- and over-predicts during injection periods. This mixed
302 performance is a result of the single proportionality constant for each dataset that does not
303 sufficiently capture the complex relationships between injection rate and seismicity. *ETAS2-*
304 *specific*, which describes the seismicity response with sleeve-specific injection data, presents
305 the best match during the periods of high seismicity rate due to pressurized fluid forcing. Here,
306 the visual comparison is very encouraging, but hinges on in-sample, sleeve-specific
307 proportionality constants between seismic rates and injection rates.

308 We next analyze the performance of all ETAS models, including the out-of-sample versions,
309 over the entire testing periods at PNR-1z (Figure 3b-d) and at PNR-2 (Figure 4b-d). Using a
310 simple acceptance/rejection criterion, we consider a forecast *accepted* (green symbols) if the
311 observations fall within the 95% model range, otherwise we mark it as *rejected* (red symbols).

312 An ideal forecast, which predicts the observations perfectly, aligns along the diagonal lines of
313 Figures 3b-d and 4b-d. While the observations fall into the 95% forecast range of the ETAS1
314 models about 80% of the time, these matches correspond to periods of low seismicity: accepted
315 forecasts occur only when less than 40 events are observed at PNR-1z (Figure 3b,c) and less
316 than 150 events are observed at PNR-2 (Figure 4b,c). We also note that (1) at both PNR-1z and
317 PNR-2 *ETAS1-global* overpredicts less frequently than models parameterized on well-specific
318 seismicity when the seismicity rate is extremely low (Figure 3b,c and Figure 4b,c) but
319 underpredicts more during high-rate windows, and (2) in PNR-2 the differences between

320 *ETAS1-optimized* and *ETAS1-unoptimized* are negligible (Figure 4b), a result of the similar
321 parameters estimated from the two wells (Table S2).

322 The performance of the ETAS2 class (Figures 3d and 4d) differs from ETAS1 mostly during
323 injection periods, and the improvement is appreciable. *ETAS2-specific* performs strikingly
324 well, as the only model to forecast very productive periods with more than 300 events at PNR-
325 1z (Figure 3d) and more than 1,000 events at PNR-2 (Figure 4d). Finally, the out-of-sample
326 *ETAS2-unoptimized* model, which uses the bulk seismic response to injection at PNR-1z to
327 forecast seismicity at PNR-2, persistently underpredicts injection-induced high rates (Figure
328 4d), but its underprediction is less severe than that of the ETAS1 class.

329

330 **Likelihood scores**

331 The cumulative log-likelihood scores of the models over the entire duration of the PNR
332 catalogs show that the injection-rate driven ETAS2 realizations considerably outperform
333 models belonging to the standard ETAS1 class (Figure 5). In particular, *ETAS2-specific* has
334 the highest likelihood scores at both wells and thus ranks as the best performing model,
335 followed by *ETAS2-bulk* as second-best. The latter performs unevenly in the two wells, with
336 better predictive skill in PNR-1z (Figure 5a) than in PNR-2 (Figure 5b) during the first few
337 days of operations. Encouragingly, the out-of-sample *ETAS2-unoptimized* model scores better
338 than all ETAS1 models and performs similarly to *ETAS2-bulk* during the first week of
339 treatment of PNR-2. In other words, a model calibrated on PNR-1z data could have provided
340 informative forecasts for PNR-2.

341 *ETAS1-global* performs worse than the injection-rate driven ETAS2 class but compares well
342 with the other ETAS1 models and even with the *ETAS2-unoptimized* and *ETAS2-bulk* models
343 in the early stages of PNR-2 (inset of Figure 5b); this is a priori surprising for a model calibrated
344 on moderate to large subduction zone earthquakes.

345

346 **Conclusions**

347 The PNR microseismic datasets present a unique opportunity to develop and evaluate statistical
348 forecasting models of hydraulic fracturing induced seismicity. Notwithstanding the variability
349 and uncertainties linking pumping data to the induced seismicity response at both PNR wells,
350 we observe a generally positive co-dependency between seismicity and injection rates that
351 supports the incorporation of operational parameters into the standard tectonic ETAS model.

352 In comparing the performance of the standard and injection-rate driven ETAS forecasts, we
353 find that the seismicity decay after the operations, or between stages, is satisfactorily captured
354 by the standard ETAS. We interpret this result as follows. During operations we witness the
355 complex interplay of rapid pore pressure effects and earthquake clustering, expressing a variety
356 of possible mechanisms (*e.g.*, elastostatic stress transfer, poroelastic effects, aseismic creep)
357 (*Schultz et al.*, 2020), while external forcing ceases in inter- and post-injection periods and
358 seismicity shows a more typical tectonic behavior.

359 However, the log-likelihood scores of the ETAS models demonstrate that a non-stationary
360 background rate tied to the injection rate is necessary to avoid severe underpredictions during
361 injection periods, when the seismic productivity is high. Thus, even a simplistic linear
362 relationship between injection rate and induced seismicity leads to informative ETAS forecasts
363 in HF environments. From the model comparison, we conclude that (1) bulk constants of
364 proportionality do not accurately describe the variable seismic response to fluid injection, and
365 (2) a sleeve-specific modulation of the seismic response to injection is the most critical element
366 for producing reliable forecasts.

367 In our study, the best-performing ETAS model is an in-sample forecast that represents a best-
368 case scenario. This performance may be difficult to attain out-of-sample. However, the sleeve-
369 specific constants of proportionality could be estimated and fine-tuned in near real-time

370 conditions from the initial seismic response at the sleeve, similarly to real-time attempts to
371 estimate parameters of other models (e.g., *Clarke et al.*, 2019). Given (1) the temporal
372 variability of the seismic response to constant injection and (2) the time-varying catalog
373 completeness thresholds, the parameters will doubtlessly be more uncertain, and this additional
374 uncertainty should be propagated into the forecasts. In this regard, the operator would have to
375 assume that (i) the injection rate at each sleeve is known in advance and (ii) the evolving sleeve-
376 specific seismic response is continuously acquired and adequately detected to support frequent
377 model calibrations.

378 To mimic real-time conditions (*i.e.*, before data are available for parameter estimation), we also
379 evaluate forecasts from three out-of-sample models. Although their performance is worse than
380 the in-sample models, we also see encouraging results. The models present low log-likelihood
381 scores in the longer term (*i.e.*, more than 3-5 days after the start of operations), but they perform
382 comparably to some in-sample models during the first few days of operations. This is true even
383 for the ETAS model calibrated on data from global subduction zones. This is promising for
384 operational conditions: operators could provide forecasts during the very early stages of
385 operations using parameters that are either generic or previously calibrated on adjacent wells.
386 As well-specific and stage-specific data become available, forecasts can be improved with re-
387 estimated parameters and the operational injection data, similarly to an ETAS approach
388 proposed for other time-varying fluid-driven processes such as natural seismic swarms (*Llenos*
389 *& Michael*, 2019). To further assess the robustness of the model parameterization and
390 performance, future tests should involve datasets with a coherent magnitude scale and a less
391 time-variant magnitude completeness level.

392 In light of the results from the PNR experiments, we conclude that injection-rate driven ETAS
393 models produce informative time-dependent probabilistic seismic rate forecasts. The
394 seismicity forecasts, when convolved with models of ground motion, exposure and

395 vulnerability, can support time-dependent probabilistic seismic hazard and risk assessment.
396 These forecast models may provide useful information for operators, regulators, residents and
397 other stakeholders in HF environments.

398

399 **Data and resources**

400 The PNR-1z and PNR-2 microseismicity catalogs as well as the fluid injection rate data used
401 in this study can be acquired through access to the UK Oil and Gas Authority website at
402 <https://www.ogauthority.co.uk/exploration-production/onshore/onshore-reports-and-data/>.

403 The supplemental material attached to this manuscript illustrates examples of histograms from
404 the ETAS simulations performed for PNR-1z and PNR-2; it also provides a summary of the
405 developed ETAS models along with their parameterizations.

406

407 **Acknowledgements**

408 The authors would like to thank the UK Oil and Gas Authority (OGA) for providing the
409 datasets. SM was supported by a Great Western Four+ Doctoral Training Partnership (GW4+
410 DTP) studentship from the Natural Environment Research Council (NERC) (NE/L002434/1)
411 and by a studentship from the British Geological Survey University Funding Initiative (BUFI)
412 (S350). MJW and BB were supported by NERC (NE/R017956/1, "EQUIPT4RISK"). MJW
413 and MS were supported by the European Union H2020 program (No 821115, "RISE"). BB
414 was also supported by the NERC grant NE/R01809X/1. This work was also supported by the
415 Bristol University Microseismic ProjectS ("BUMPS") and by the Southern California
416 Earthquake Center (SCEC) (Contribution No. 10149). SCEC is funded by the National Science
417 foundation Cooperative Agreement EAR-1600087 & US Geological Survey Cooperative
418 Agreement G17AC00047.

419

420 **References**

421 Atkinson, G. M., D. W. Eton, and N. Igonin (2020). Developments in understanding seismicity
 422 triggered by hydraulic fracturing, *Nat. Rev. Earth Environ.*, 1, 264-277.
 423 <https://doi.org/10.1038/s43017-020-0049-7>.

424 Asanuma, H., T. Eto, M. Adachi, K. Saeki, K. Aoyama, H. Ozeki, and M. Häring (2014).
 425 Seismostatistical Characterization of Earthquakes from Geothermal Reservoirs.
 426 *Proceedings of the Thirty-Ninth Workshop on Geothermal Reservoir engineering Stanford*
 427 *University, Stanford, California, February 2014, SGP-TR-202.*

428 Baptie, B. and R. Luckett (2019). Seismicity Induced by Hydraulic Fracturing Operations at
 429 Preston New Road, Lancashire, 2018. *Proceedings of the Society of Earthquake and Civil*
 430 *Engineering Dynamics Conference, September 2019, Greenwich, London.*

431 Baptie, B., R. Luckett, A. Butcher, and M. J. Werner (2020). Robust relationships for
 432 magnitude conversion of PNR seismicity catalogues. *British Geological Survey Open*
 433 *Report OR/20/042, British Geological Survey for Oil and Gas Authority, London, United*
 434 *Kingdom, 32 pp.*

435 Bachmann, C., S. Wiemer, J. Woessner, and S. Hainzl (2011). Statistical analysis of the
 436 induced Basel 2006 earthquake sequence: Introducing a probability-based monitoring
 437 approach for Enhanced Geothermal Systems, *Geophys. J. Int.*, 186, 793-807.

438 Bourne, S., and S. Oates (2017). Development of statistical geomechanical models for
 439 forecasting seismicity induced by gas production from the Groningen field, *Netherlands*
 440 *Journal of geosciences*, 96(5), S175-S182. <http://doi.org.10.1017/njg.2017.35>.

441 Clarke, H., P. Turner, R. M. Bustin, N. Riley, and B. Besly (2018). Shale Gas Resources of the
 442 Bowland Basin, NW England: A Holistic Study, *Petrol. Geosci.*, 24(3), 287-322,
 443 <https://doi.org/10.1144/petgeo2017-066>.

444 Clarke, H., J. P. Verdon, T. Kettlety, A. F. Baird, and J. M. Kendall (2019). Real- Time
 445 Imaging, Forecasting, and Management of Human- Induced Seismicity at Preston New
 446 Road, Lancashire, England, *Seismol. Res. Lett.*, 90(5), 1902-1915.

- 447 Cao, A. M., and S. S. Gao (2002). Temporal variation of seismic b- values beneath
448 northeastern Japan island arc, *Geophys. Res. Lett.*, 29(9), 1334.
449 <https://doi.org/10.1029/2001GL013775>.
- 450 Cremen, G. and M. J. Werner (2020). A Novel Approach to Assessing Nuisance Risk from
451 Seismicity Induced by UK Shale Gas Development, with Implications for Future Policy
452 Design, *Nat. Hazards Earth Syst. Sci. Discuss.*, <https://doi.org/10.5194/nhess-2020-95>.
- 453 Cuadrilla Resources Inc. (2019). Hydraulic Fracture Plan PNR 2. Cuadrilla Resources Inc.
454 Report CORP-HSE-RPT-003.
- 455 Ellsworth, W. L. (2013). Injection-induced earthquakes, *Science*, 341(6142), 1225942.
456 <https://doi.org/10.1126/science.1225942>
- 457 Ellsworth, W. L., D. Giardini, J. Townend, S. Ge, and T. Shimamoto (2019). Triggering of the
458 Pohang, Korea, Earthquake (Mw 5.5) by Enhanced Geothermal System Stimulation,
459 *Seismol. Res. Lett.*, 90(5), 1844-1858.
- 460 Hainzl, S., and Y. Ogata (2005). Detecting fluid signals in seismicity data through statistical
461 earthquake modeling, *J. Geophys. Res. Solid Earth*, 110(B5).
- 462 Harte, D. (2015). Log-likelihood of earthquake models: evaluation of models and forecasts,
463 *Geophys. J. Int.*, 201, 711-723, <https://doi.org/10.1093/gji/ggu442>.
- 464 Jia, K., S. Zhou, J. Zhuang, C. Jiang, Y. Guo, Z. Gao, S. Gao, Y. Ogata, and X. Song (2020).
465 Nonstationary Background Seismicity Rate and Evolution of Stress Changes in the
466 Changning Salt Mining and Shale-Gas Hydraulic Fracturing Region, Sichuan Basin, China,
467 *Seismol. Res. Lett.* 91, 2170–2181, <https://doi.org/10.1785/0220200092>.
- 468 Kagan, Y. Y. (2010). Statistical distribution of earthquake numbers: consequence of branching
469 process, *Geophys. J. Int.*, 180, 1313-1328, [https://doi.org/10.1111/j.1365-
470 246X.2009.04487.x](https://doi.org/10.1111/j.1365-246X.2009.04487.x).
- 471 Keranen, K. M., H. M. Savage, G. A. Abers, and E. S. Cochran (2013). Potentially induced
472 earthquakes in Oklahoma, USA: Links between wastewater injection and the 2011 Mw 5.7
473 earthquake sequence, *Geology*, <https://doi.org/10.1130/G34045.1>.

- 474 Kettlety, T., J. P. Verdon, M. J. Werner, and J. M. Kendall (2020a). Stress transfer from
 475 opening hydraulic fractures controls the distribution of induced seismicity, *J. Geophys. Res.*
 476 *Solid Earth*, 125, e2019JB018794, <https://doi.org/10.1029/2019JB018794>.
- 477 Kettlety, T., J. P. Verdon, A. Butcher, M. Hampson, and L. Craddock (2020b). High-resolution
 478 imaging of the ML 2.9 August 2019 earthquake in Lancashire, United Kingdom, induced
 479 by hydraulic fracturing during Preston New Road PNR-2 operations, *Seismol. Res. Lett.*,
 480 92(1), 151-169, <https://doi.org/10.1785/0220200187>.
- 481 Kiraly-Proag, E., J. D. Zechar, V. Gischig, S. Wiemer, D. Karvounis, and J. Doetsch (2016).
 482 Validating induced seismicity forecast models—Induced Seismicity Test Bench, *J.*
 483 *Geophys. Res. Solid Earth*, 121, 6009–6029, <https://doi.org/10.1002/2016JB013236>.
- 484 Lee, K., W. L. Ellsworth, D. Giardini, J. Townend, S. Ge, T. Shimamoto, I. Yeo, T. Kang, J.
 485 Rhie, D. Sheen, C. Chang, J. Woo, and C. Langenbruch (2019). Managing injection-induced
 486 seismic risks, *Science*, 364 (6442), 730–32.
- 487 Lei, X., D. Huang, J. Su, G. Jiang, X. Wang, H. Wang, X. Guo, and H. Fu (2017). Fault
 488 reactivation and earthquakes with magnitudes of up to Mw4.7 induced by shake-gas
 489 hydraulic fracturing in Sichuan Basin, China, *Sci. Rep.*, 7 (7971).
 490 <https://doi.org/10.1038/s41598-017-08557-y>.
- 491 Lei, X., Z. Wang, and J. Su (2019). The December 2018 ML 5.7 and January 2019 ML 5.3
 492 earthquakes in South Sichuan Basin induced by shale gas hydraulic fracturing, *Seismol. Res.*
 493 *Lett.* 90(3), 1099–1110. <https://doi.org/10.1785/0220190029>.
- 494 Llenos, A. L., and A. J. Michael (2013). Modeling earthquake rate change in Oklahoma and
 495 Arkansas: possible signatures of induced seismicity, *Bull. Seismol. Soc. Am.*, 103(5), 2850-
 496 2861. <https://doi.org/10.1785/0120130017>.
- 497 Llenos, A. L., and A. J. Michael (2019), Ensembles of ETAS models provide optimal
 498 operational earthquake forecasting during swarms: Insights from the 2015 San Ramon,
 499 California swarm, *Bull. Seismol. Soc. Am.*, 109, 2145-2158.
 500 <https://doi.org/10.1785/0120190020>.
- 501 Mena, B., S. Wiemer and C. Bachmann (2013). Building robust models to forecast the induced
 502 seismicity related to geothermal reservoir enhancement, *Bull. Seismol. Soc. Am.*, 103(1),
 503 383-392. <https://doi.org/10.1785/0120120102>.

- 504 Michael, A. J., and M. J. Werner (2018). Preface to the Focus Section on the Collaboratory for
505 the Study of Earthquake Predictability (CSEP): New Results and Future Directions, *Seismol.*
506 *Res. Lett.*, 89(4), 1226-1228. <https://doi.org/10.1785/0220180161>.
- 507 Ogata, Y. (1988). Statistical models for earthquake occurrences and residual analysis for point
508 processes, *J. Am. Stat. Assoc.*, 83(401), 9–27. 2861–2864.
- 509 Seif, S., A. Mignan, J. D. Zechar, M. J. Werner, and S. Wiemer (2017). Estimating ETAS: The
510 effects of truncation, missing data, and model assumptions, *J. Geophys. Res. Solid Earth*
511 121, 449–469. <https://doi.org/10.1002/2016JB012809>.
- 512 Shapiro, S. A., C. Dinske, and J. Kummerow (2007). Probability of a given-magnitude
513 earthquake induced by a fluid injection, *Geophys. Res. Lett.*, 34, L22, 314,
514 <https://doi.org/10.1029/2007GL031615>.
- 515 Schultz, R., R. J. Skoumal, M. R. Brudzinski, D. Eaton, B. Baptie, and W. Ellsworth (2020).
516 Hydraulic fracturing- induced seismicity, *Rev. Geophys.*, 58, e2019RG000695.
517 <https://doi.org/10.1029/2019RG000695>.
- 518 Utsu, T. (1961). A statistical study on the occurrence of aftershocks, *Geophys. Mag.*, 30, 521-
519 605.
- 520 Verdon, J., and J. Budge (2018). Examining the Capability of Statistical Models to Mitigate
521 Induced Seismicity during Hydraulic Fracturing of Shale Gas Reservoirs, *Bull. Seismol.*
522 *Soc. Am.*, 108(2), 690-701. <https://doi.org/10.1785/0120170207>
- 523 Woessner, J., L. Danciu, D. Giardini, H. Crowley, F. Cotton, G. Grünthal, G. Valensise, R.
524 Arvidsson, R. Basili, M. Betül Demircioglu, S. Hiemer, C. Meletti, R. Musson, A. Rovida,
525 K. Sesetyan, M. Stucchi, and the Seismic Hazard Harmonization in Europe (SHARE)
526 Consortium (2015). The 2013 European Seismic hazard model: key components and results,
527 *Bull. Earth. Eng.* <https://doi.org/10.1007/s10518-015-9795-1>.
- 528 Zechar, J.D. (2010). Evaluating earthquake predictions and earthquake forecasts: a guide for
529 students and new researchers, *Community Online Resource for Statistical Seismicity*
530 *Analysis*, <https://doi.org/10.5078/corssa-77337879>.

531 Zhang, L., M. J. Werner, and K. Goda (2020). Variability of ETAS parameters in global
532 subduction zones and applications to mainshock-aftershock hazard assessment, *Bull.*
533 *Seismol. Soc. Am.*, 110(1), 191-212. <https://doi.org/10.1785/0120190121>.

534 Zhuang, J., Y. Ogata, and D. Vere-Jones (2002). Stochastic declustering of space-time
535 earthquake occurrences, *J. Am. Stat. Assoc.*, 97(458), 369–380.
536 <https://doi.org/10.1198/016214502760046925>.

537 Zhuang, J., D. Harte, M. J. Werner, S. Hainzl, and S. Zhou (2012). Basic models of seismicity:
538 temporal models, *Community Online Resource for Statistical Seismicity Analysis*.
539 <https://doi.org/10.5078/corssa-79905851>.

540 Zhuang, J., and S. Touati (2015). Stochastic simulation of earthquake catalogs, *Community*
541 *Online Resource for Statistical Seismicity Analysis*. [https://doi.org/10.5078/corssa-](https://doi.org/10.5078/corssa-43806322)
542 [43806322](https://doi.org/10.5078/corssa-43806322).

543

544 **Addresses of authors**

545 Simone Mancini (simone@bgs.ac.uk), British Geological Survey, The Lyell Center, Research
546 Avenue South, EH14 4AP, Edinburgh, UK

547 Maximilian Jonas Werner (max.werner@bristol.ac.uk), School of Earth Sciences, University
548 of Bristol, BS8 1RL Bristol, UK

549 Margarita Segou (msegou@bgs.ac.uk), British Geological Survey, The Lyell Center, Research
550 Avenue South, EH14 4AP, Edinburgh, UK

551 Brian Baptie (bbap@bgs.ac.uk), British Geological Survey, The Lyell Center, Research
552 Avenue South, EH14 4AP, Edinburgh, UK

553

554 **List of Figure Captions**

555 **Figure 1.** Map view of earthquakes recorded during hydraulic fracturing at the Preston New
556 Road unconventional shale gas site. Events are color-coded by the associated injection stage
557 and their size scales with magnitude. (a) Seismicity between 15 October and 17 December
558 2018 during and after injection at the PNR-1z well. (b) Seismicity between 15 August and 2
559 October 2019 during and after injection at the PNR-2 well; grey dots indicate the epicenters of
560 events occurred during operations at PNR-1z. The black lines represent the surface projection

561 of the two wellpaths. Diamonds illustrate the position of the main sleeves worked during the
 562 operations at the two wells and are colored by the corresponding injection stages.

563

564 **Figure 2.** Seismicity response to hydraulic fracturing at the Preston New Road site. (a-b)
 565 Histograms of the number of $M \geq -1.5$ events per hour (black bars) as a function of time during
 566 operations along with the cumulative volume of injected fluid (light blue line) at PNR-1z and
 567 PNR-2, respectively. For illustration purposes, we inserted a time gap during the pause of
 568 operations at PNR-1z, which is indicated by the grey area. (c-e) Examples of seismic
 569 productivity and earthquake magnitudes vs. time (red circles) in response to the injection
 570 history (light blue line) at selected sleeves.

571

572 **Figure 3.** Observed vs. forecasted number of $M \geq -1.5$ events at PNR-1z. (a) Illustration of
 573 incremental 1-hour forecast timeseries vs. observations at PNR-1z injection sleeves
 574 characterized by weak and strong seismicity response as well as during the pause of operations.
 575 ETAS2-*bulk* model predictions are shown only during injection periods indicated by the “Inj.”
 576 label (otherwise its forecasts are identical to ETAS1-*optimized* and ETAS2-*specific*). Black
 577 circles indicate the number of observed events in each forecast window. Other symbols
 578 represent the mean expected number from the simulations. Bars denote 95% ETAS model
 579 simulation ranges. For illustration purposes, during periods of suspended/paused injection data
 580 are plotted at 12-hour intervals. (b-d) Observed vs. expected number of events per forecast
 581 period over all injection stages. Each symbol indicates one forecast window, which is accepted
 582 if the 95% model range (black vertical bars) intersect the diagonal black line. Red symbols
 583 denote rejected forecasts (data outside model range); green symbols denote accepted forecasts.

584

585

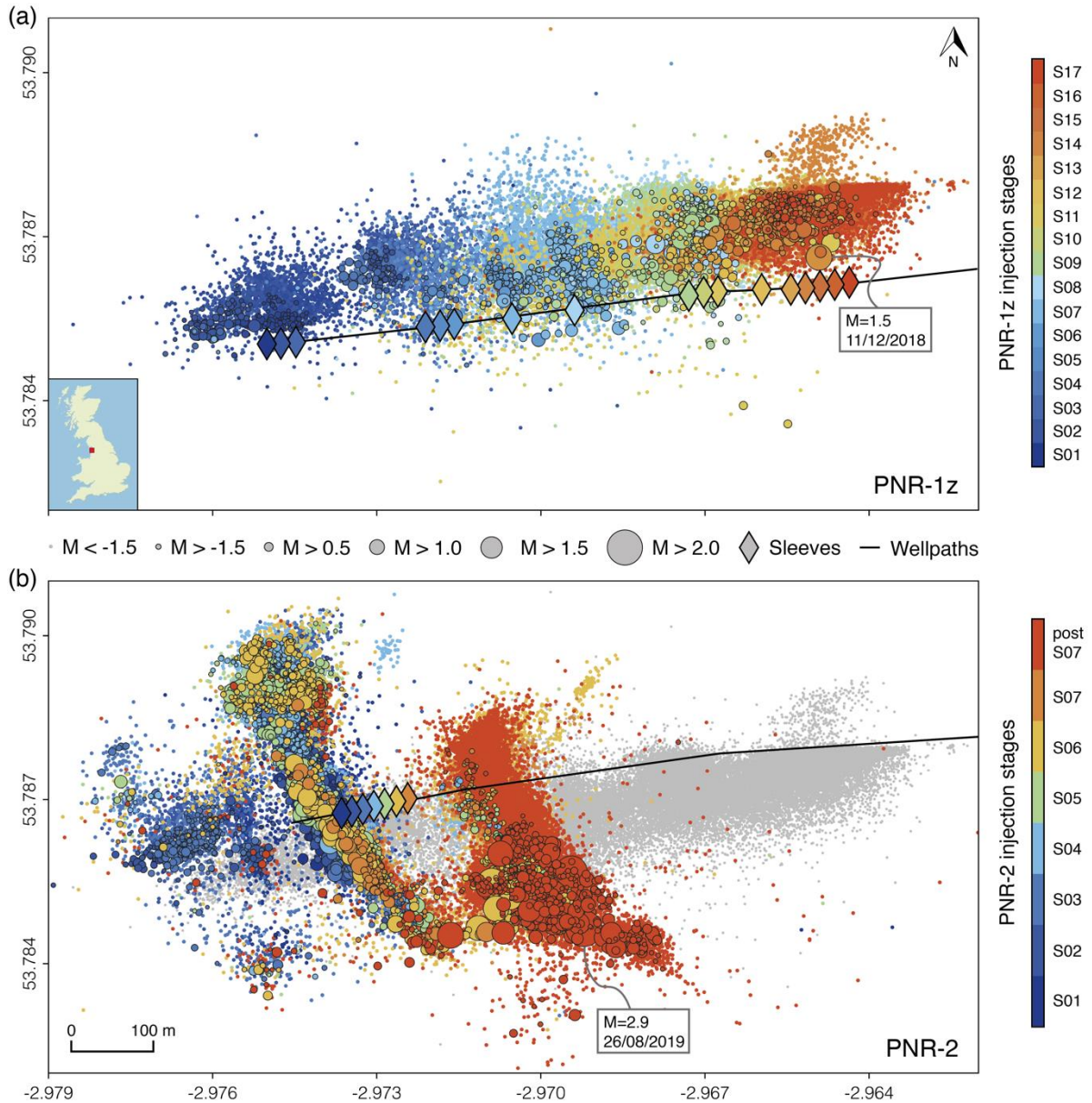
586 **Figure 4.** Observed vs. forecasted number of $M \geq -1.5$ events at PNR-2. (a) Illustration of
 587 incremental 1-hour forecast timeseries vs. observations at PNR-2 injection sleeves
 588 characterized by weak and strong seismicity response as well as during the pause of operations.
 589 ETAS2-*bulk* model predictions are shown only during injection periods indicated by the “Inj.”
 590 label (otherwise its forecasts are identical to ETAS1-*optimized* and ETAS2-*specific*). Black
 591 circles indicate the number of observed events in each forecast window. Other symbols
 592 represent the mean expected number from the simulations. Bars denote 95% ETAS model
 593 simulation ranges. For illustration purposes, during periods of suspended/paused injection data
 594 are plotted at 2-hour intervals. (b-d) Observed vs. expected number of events per forecast
 595 period over all injection stages. Each symbol indicates one forecast window, which is accepted
 596 if the 95% model range (black vertical bars) intersect the diagonal black line. Red symbols
 597 denote rejected forecasts (data outside model range); green symbols denote accepted forecasts.

598

599 **Figure 5.** Cumulative log-likelihood timeseries. ETAS models tested on (a) PNR-1z and (b)
 600 PNR-2.

601

602 **Figures with captions**

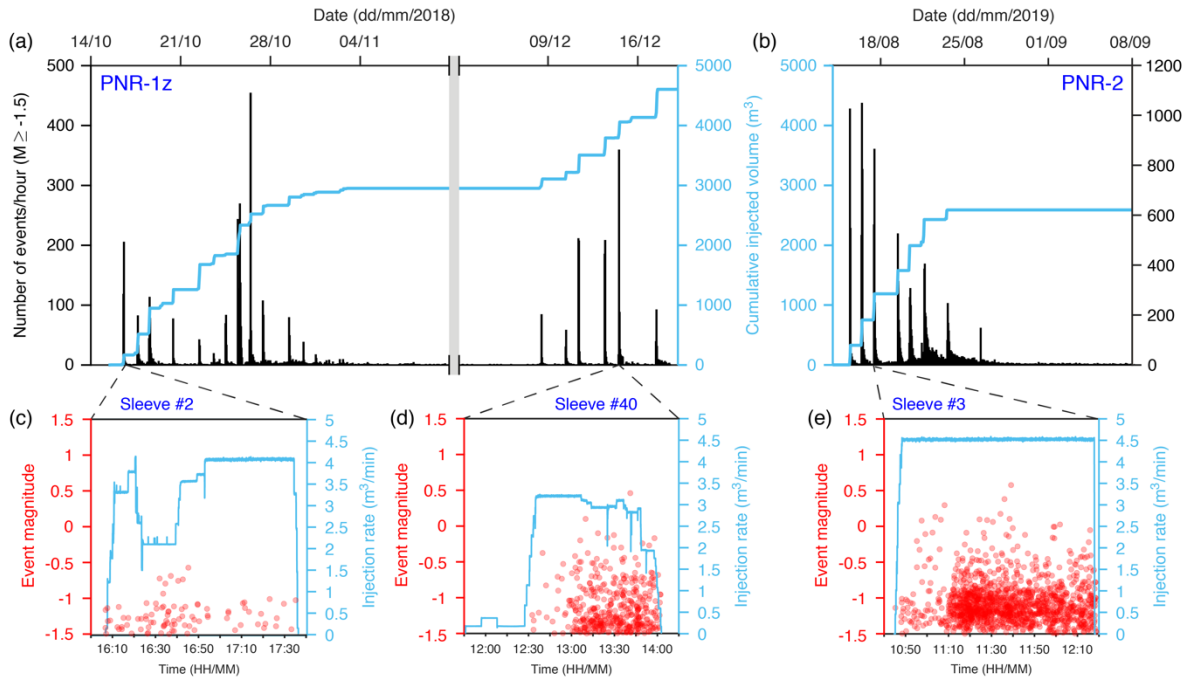


603

604 **Figure 1.** Map view of earthquakes recorded during hydraulic fracturing at the Preston New
 605 Road unconventional shale gas site. Events are color-coded by the associated injection stage
 606 and their size scales with magnitude. (a) Seismicity between 15 October and 17 December
 607 2018 during and after injection at the PNR-1z well. (b) Seismicity between 15 August and 2
 608 October 2019 during and after injection at the PNR-2 well; grey dots indicate the epicenters of
 609 events occurred during operations at PNR-1z. The black lines represent the surface projection
 610 of the two wellpaths. Diamonds illustrate the position of the main sleeves worked during the
 611 operations at the two wells and are colored by the corresponding injection stages.

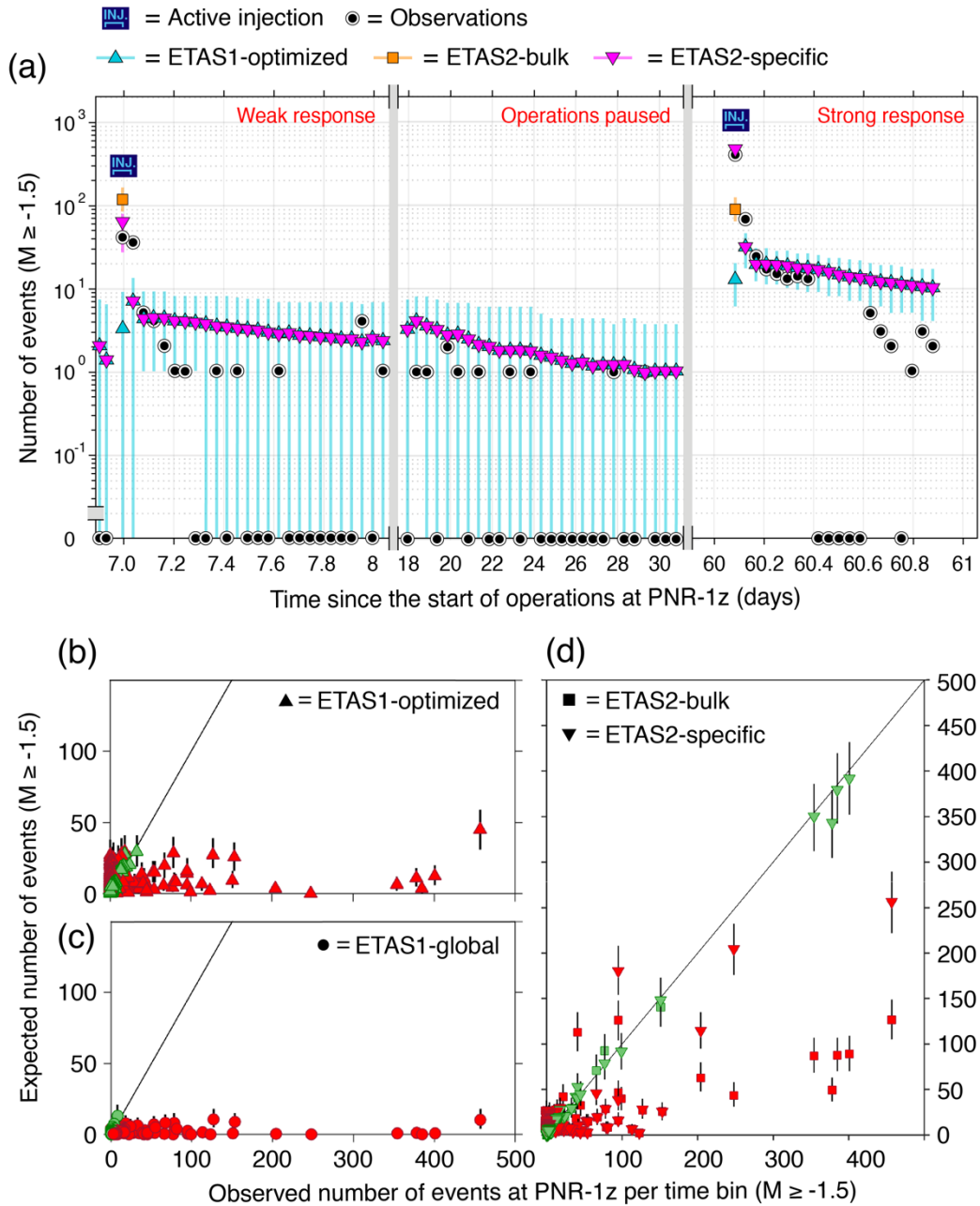
612

613



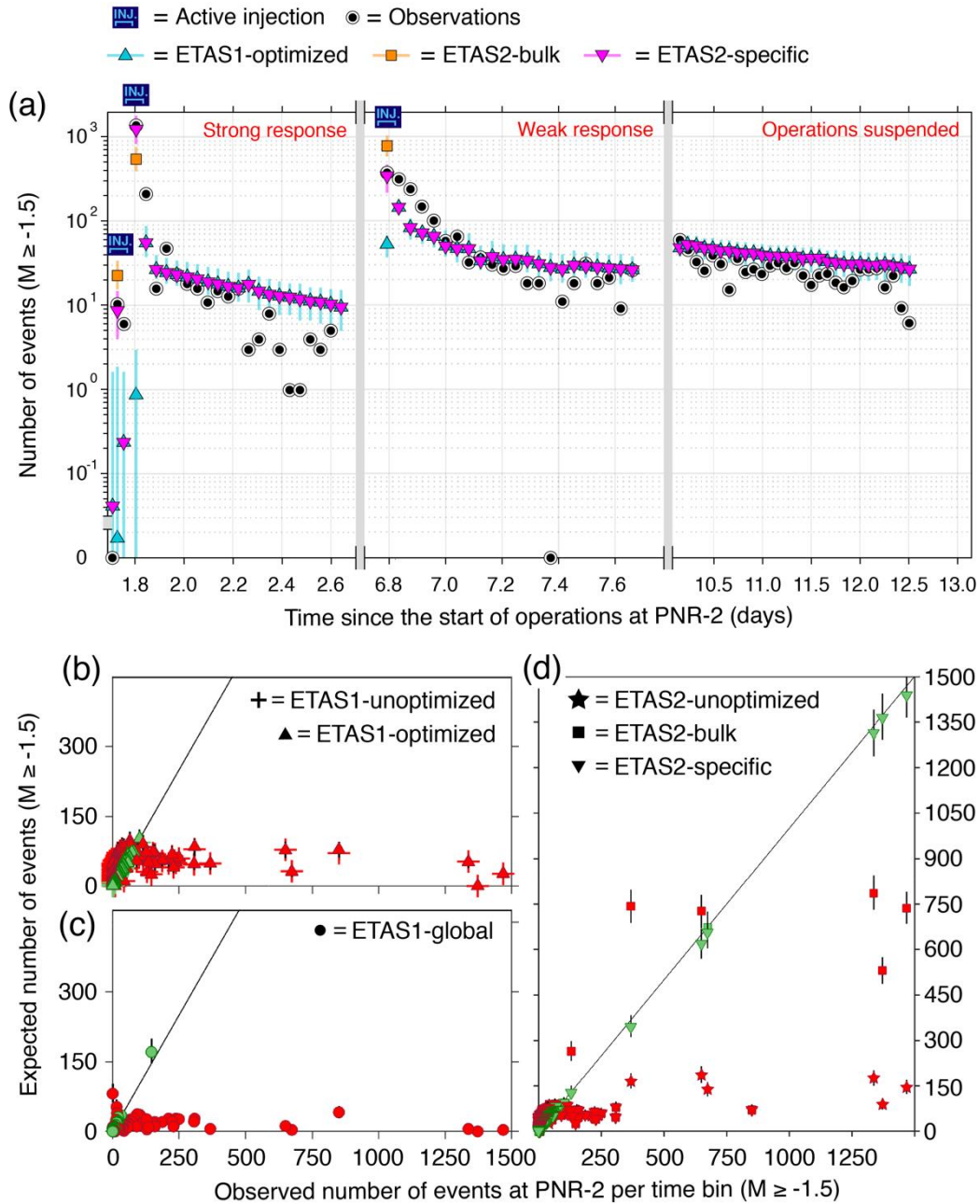
614
 615 **Figure 2.** Seismicity response to hydraulic fracturing at the Preston New Road site. (a-b)
 616 Histograms of the number of $M \geq -1.5$ events per hour (black bars) as a function of time during
 617 operations along with the cumulative volume of injected fluid (light blue line) at PNR-1z and
 618 PNR-2, respectively. For illustration purposes, we inserted a time gap during the pause of
 619 operations at PNR-1z, which is indicated by the grey area. (c-e) Examples of seismic
 620 productivity and earthquake magnitudes vs. time (red circles) in response to the injection
 621 history (light blue line) at selected sleeves.

622
 623
 624
 625
 626
 627
 628
 629
 630
 631
 632



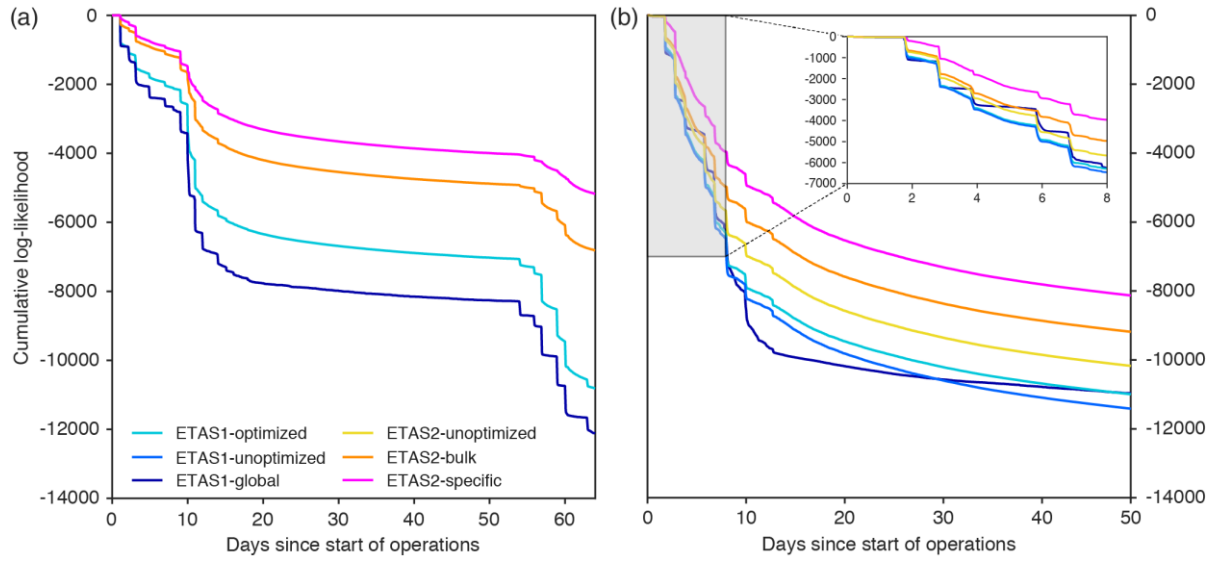
633

634 **Figure 3.** Observed vs. forecasted number of $M \geq -1.5$ events at PNR-1z. (a) Illustration of
 635 incremental 1-hour forecast timeseries vs. observations at PNR-1z injection sleeves
 636 characterized by weak and strong seismicity response as well as during the pause of operations.
 637 ETAS2-*bulk* model predictions are shown only during injection periods indicated by the “Inj.”
 638 label (otherwise its forecasts are identical to ETAS1-*optimized* and ETAS2-*specific*). Black
 639 circles indicate the number of observed events in each forecast window. Other symbols
 640 represent the mean expected number from the simulations. Bars denote 95% ETAS model
 641 simulation ranges. For illustration purposes, during periods of suspended/paused injection data
 642 are plotted at 12-hour intervals. (b-d) Observed vs. expected number of events per forecast
 643 period over all injection stages. Each symbol indicates one forecast window, which is accepted
 644 if the 95% model range (black vertical bars) intersect the diagonal black line. Red symbols
 645 denote rejected forecasts (data outside model range); green symbols denote accepted forecasts.



646

647 **Figure 4.** Observed vs. forecasted number of $M \geq -1.5$ events at PNR-2. (a) Illustration of
 648 incremental 1-hour forecast timeseries vs. observations at PNR-2 injection sleeves
 649 characterized by weak and strong seismicity response as well as during the pause of operations.
 650 ETAS2-*bulk* model predictions are shown only during injection periods indicated by the “Inj.”
 651 label (otherwise its forecasts are identical to ETAS1-*optimized* and ETAS2-*specific*). Black
 652 circles indicate the number of observed events in each forecast window. Other symbols
 653 represent the mean expected number from the simulations. Bars denote 95% ETAS model
 654 simulation ranges. For illustration purposes, during periods of suspended/paused injection data
 655 are plotted at 2-hour intervals. (b-d) Observed vs. expected number of events per forecast
 656 period over all injection stages. Each symbol indicates one forecast window, which is accepted
 657 if the 95% model range (black vertical bars) intersect the diagonal black line. Red symbols
 658 denote rejected forecasts (data outside model range); green symbols denote accepted forecasts.



659

660 **Figure 5.** Cumulative log-likelihood timeseries. ETAS models tested on (a) PNR-1z and (b)
 661 PNR-2.

662

Figure 1

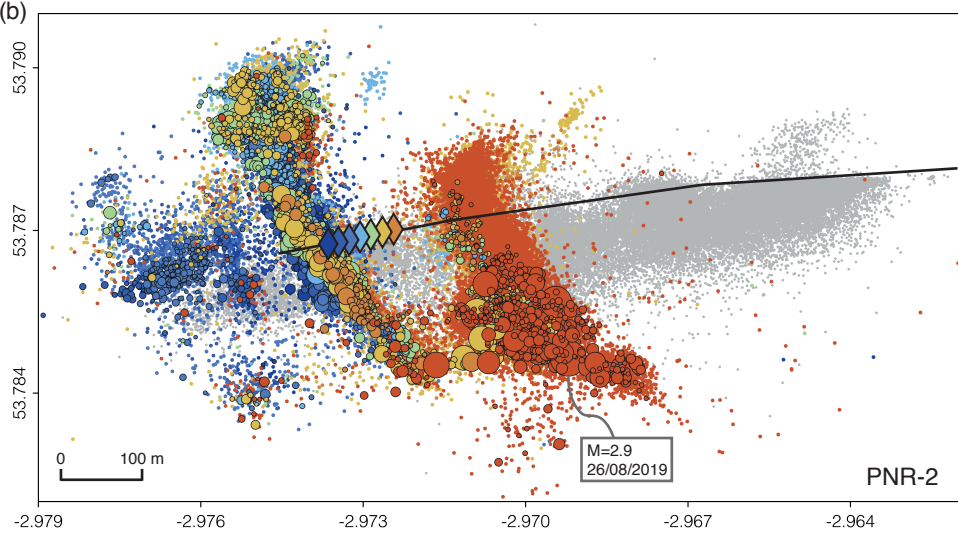
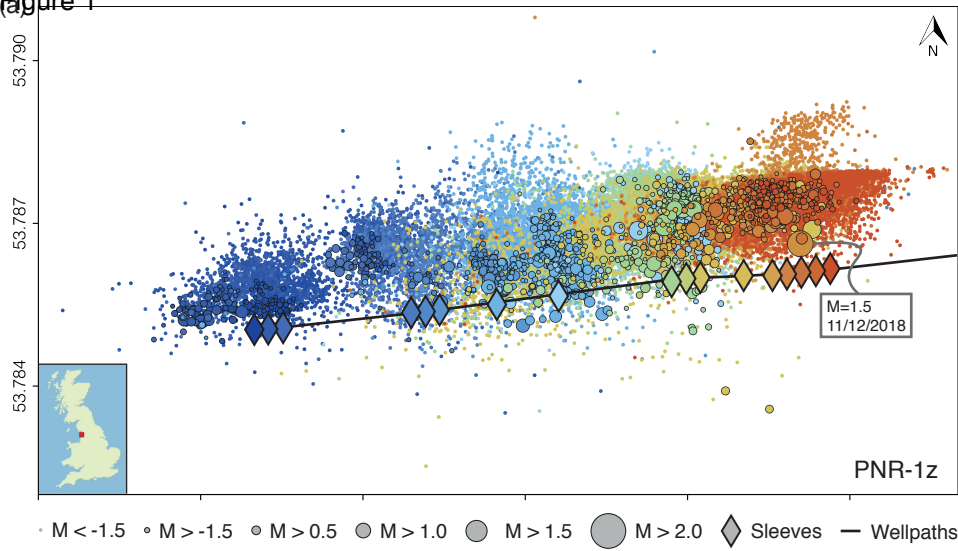


Figure 2

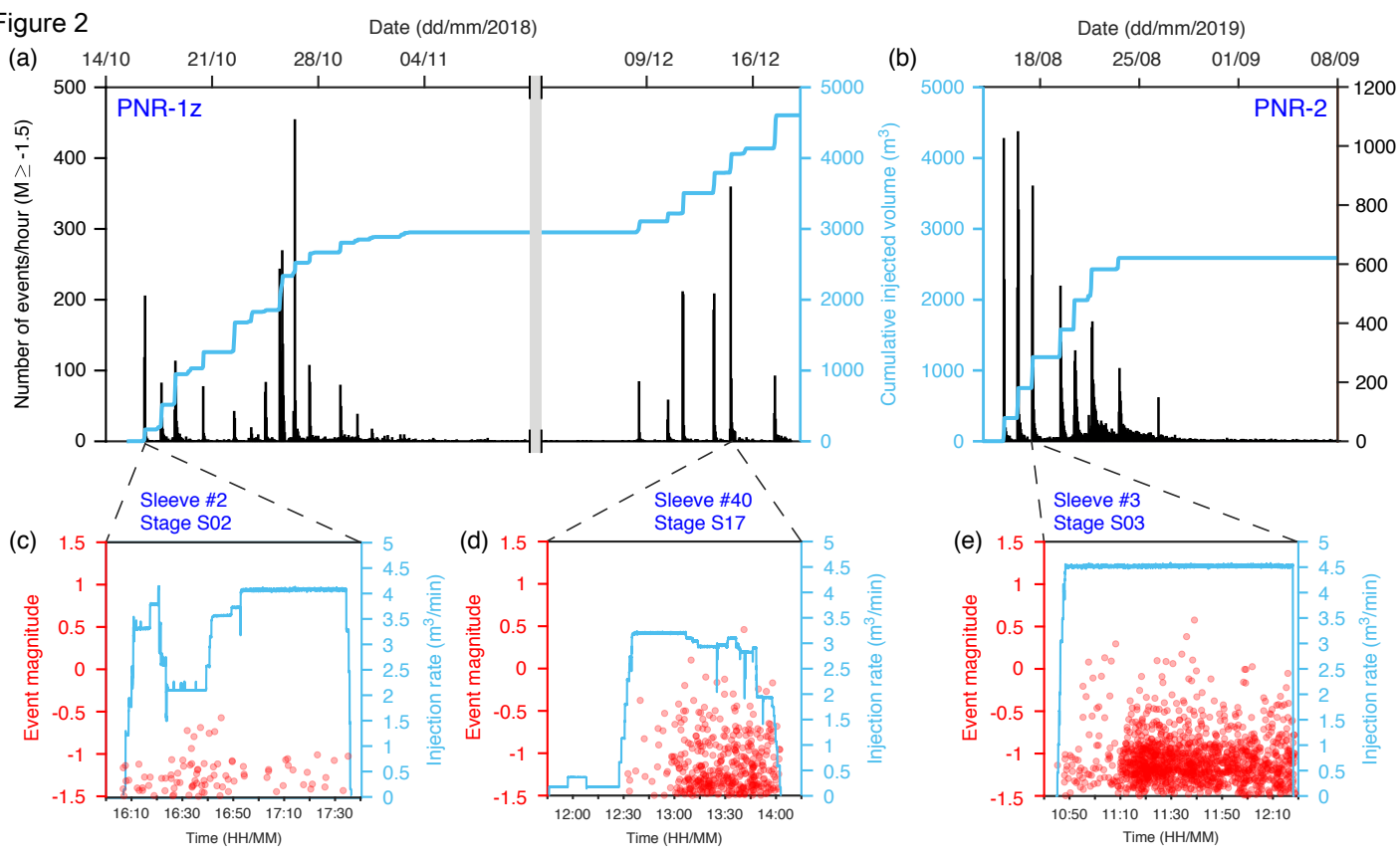




Figure 3  = Active injection  = Observations

(a)  = ETAS1-optimized  = ETAS2-bulk  = ETAS2-specific

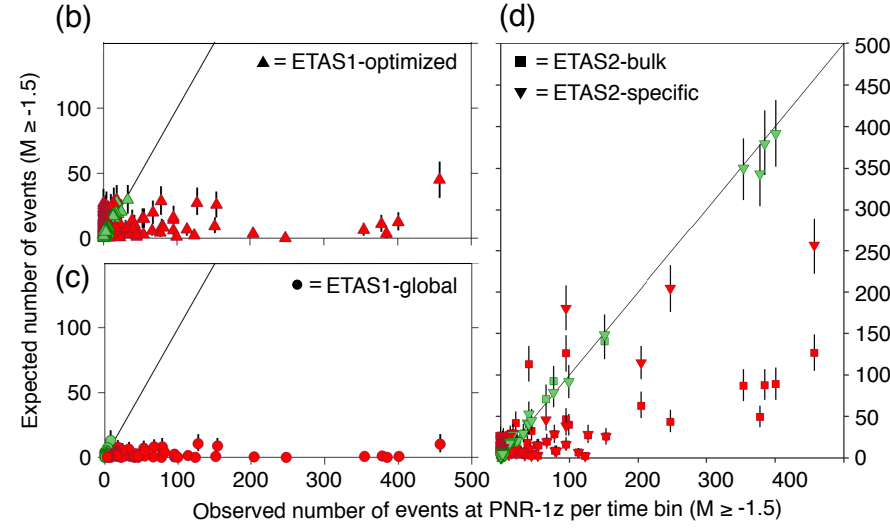
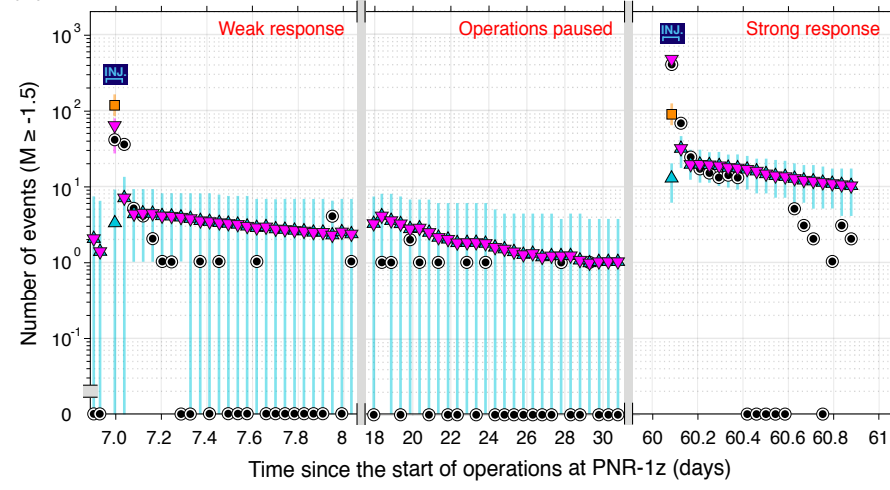


Figure 4

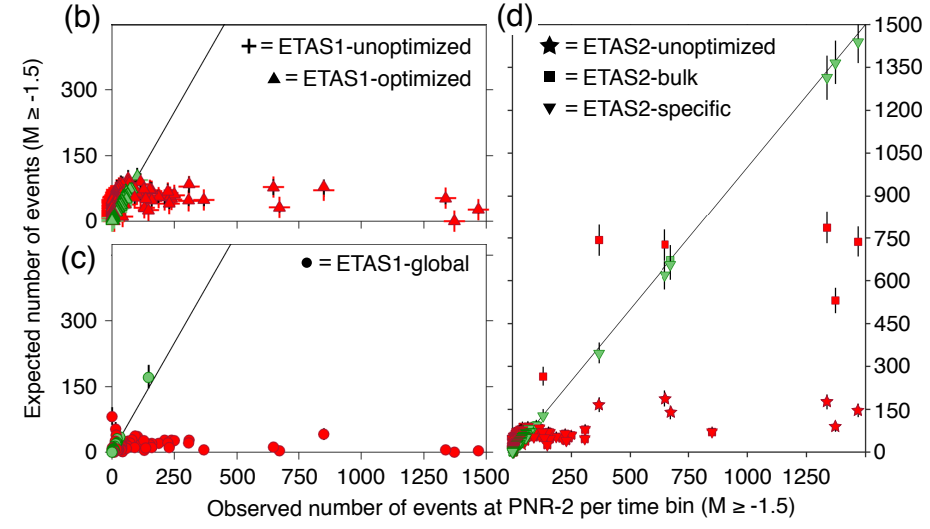
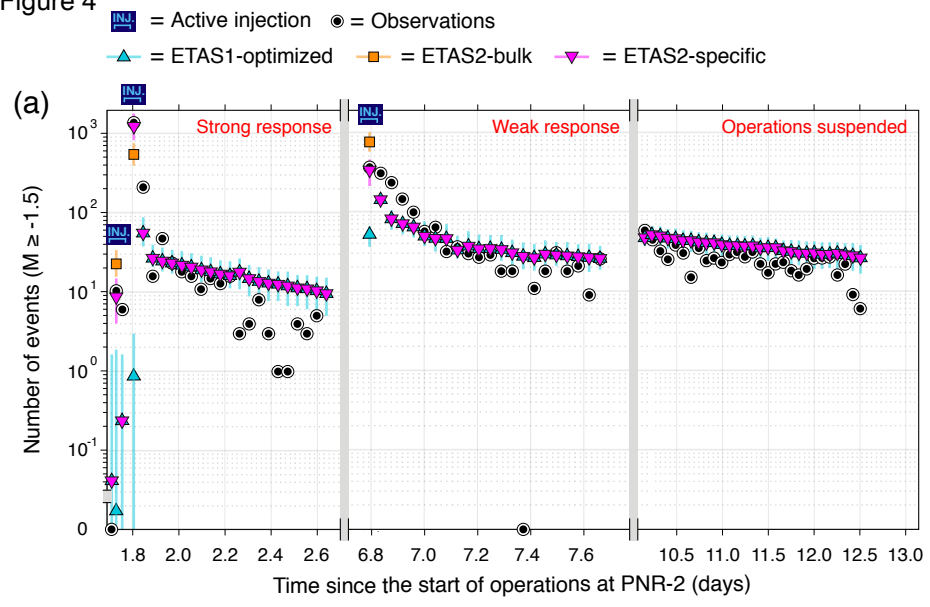
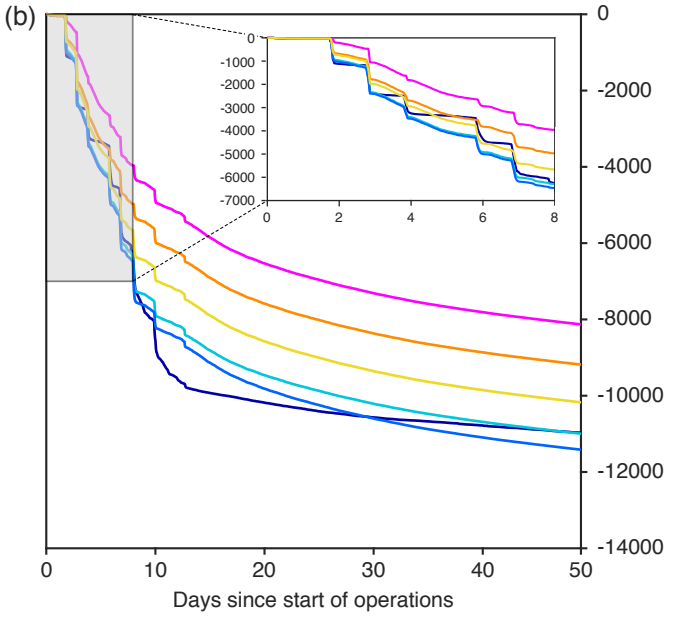
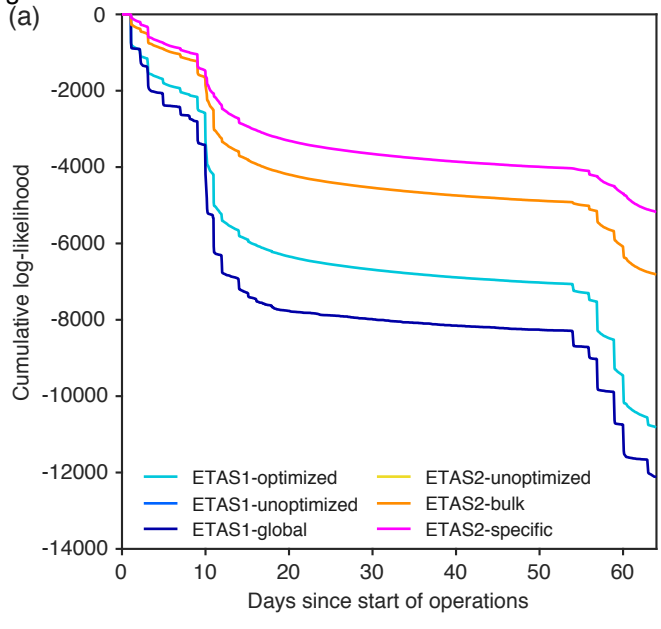


Figure 5



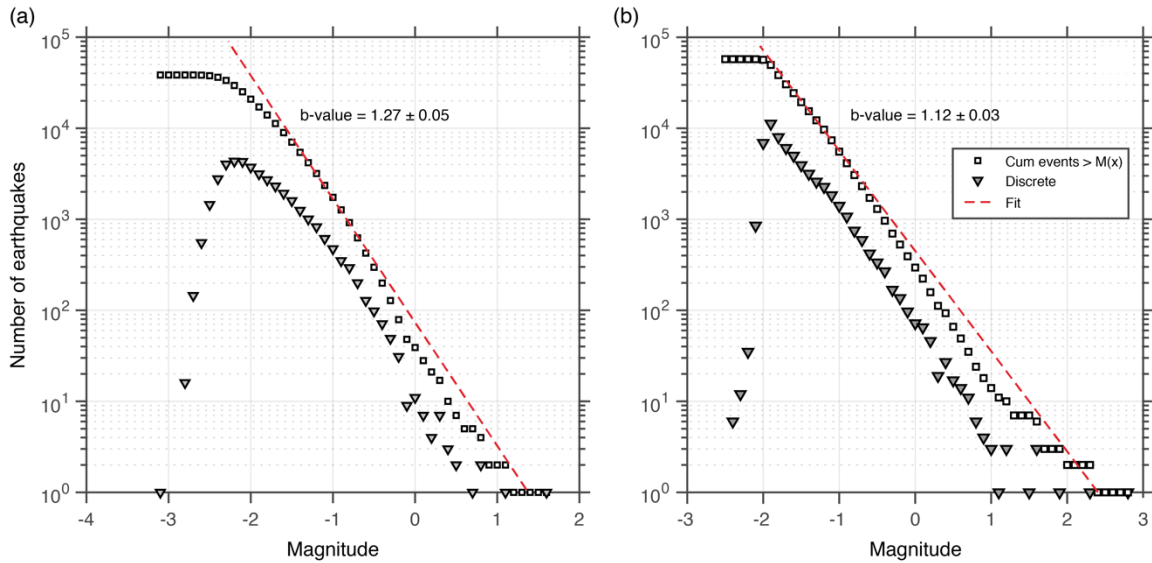
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22

Electronic Supplement to

**Probabilistic Forecasting of Hydraulic Fracturing Induced Seismicity
Using an Injection-Rate Driven ETAS Model**

by S. Mancini, M. J. Werner, M. Segou, and B. Baptie

In this supplement we first show the frequency-magnitude distributions of the catalog used in this study to calibrate the ETAS models at PNR-1z (Figure S1a) and PNR-2 (Figure S1b). We then present examples of histograms from the ETAS simulations at PNR-1z and PNR-2 (Figures S2 and S3). Finally, we report a summary of the tested ETAS versions (Table S1), and the values of the ETAS parameters (Table S2), including the bulk and sleeve-specific values of c_f (Tables S3 and S4 for PNR-1z and PNR-2, respectively).



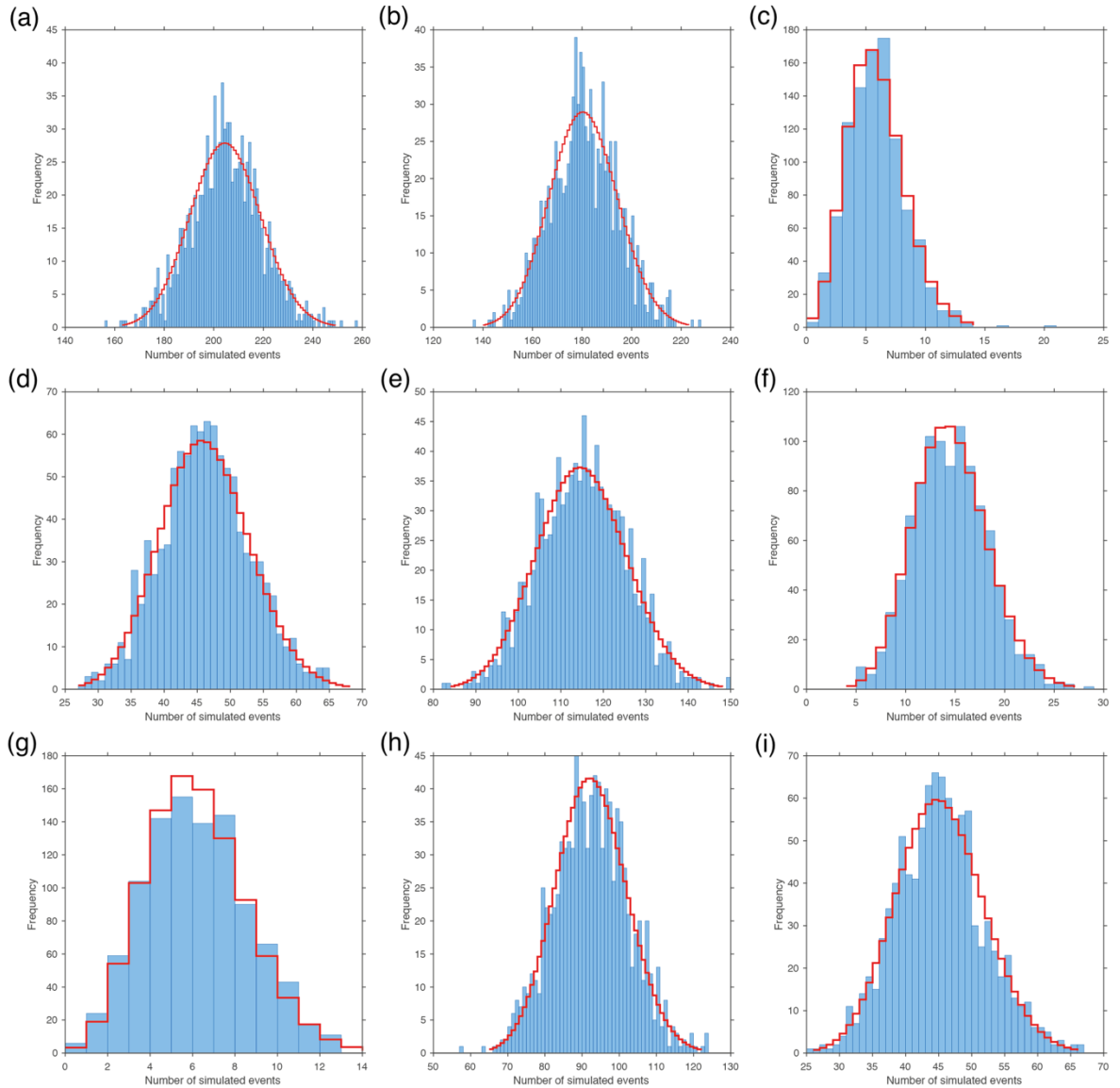
23

24 **Figure S1.** Frequency-magnitude distributions (FMD). (a) FMD for the PNR-1z catalog
 25 used in this work; (b) FMD for the full PNR-2 catalog used in this work. The red dashed
 26 line represents the Gutenberg-Richter fit to the distribution. We use the FMD to estimate
 27 the magnitude of completeness (M_c) of the catalog using the b-value stability method (*Cao*
 28 & *Gao*, 2002).

29

30 The surface network detected only larger events using local magnitudes (M_L). At PNR-2,
 31 we convert these to M_w using the conversion relationship developed by QCon for
 32 Cuadrilla's hydraulic fracturing plan (*Cuadrilla Resources Inc.*, 2019). However, the same
 33 relationship does not hold for PNR-1z (*Baptie et al.*, 2020); in that case, we replace the
 34 downhole $M_w \geq 0.0$ values with the corresponding M_L from the surface catalog.

35



36

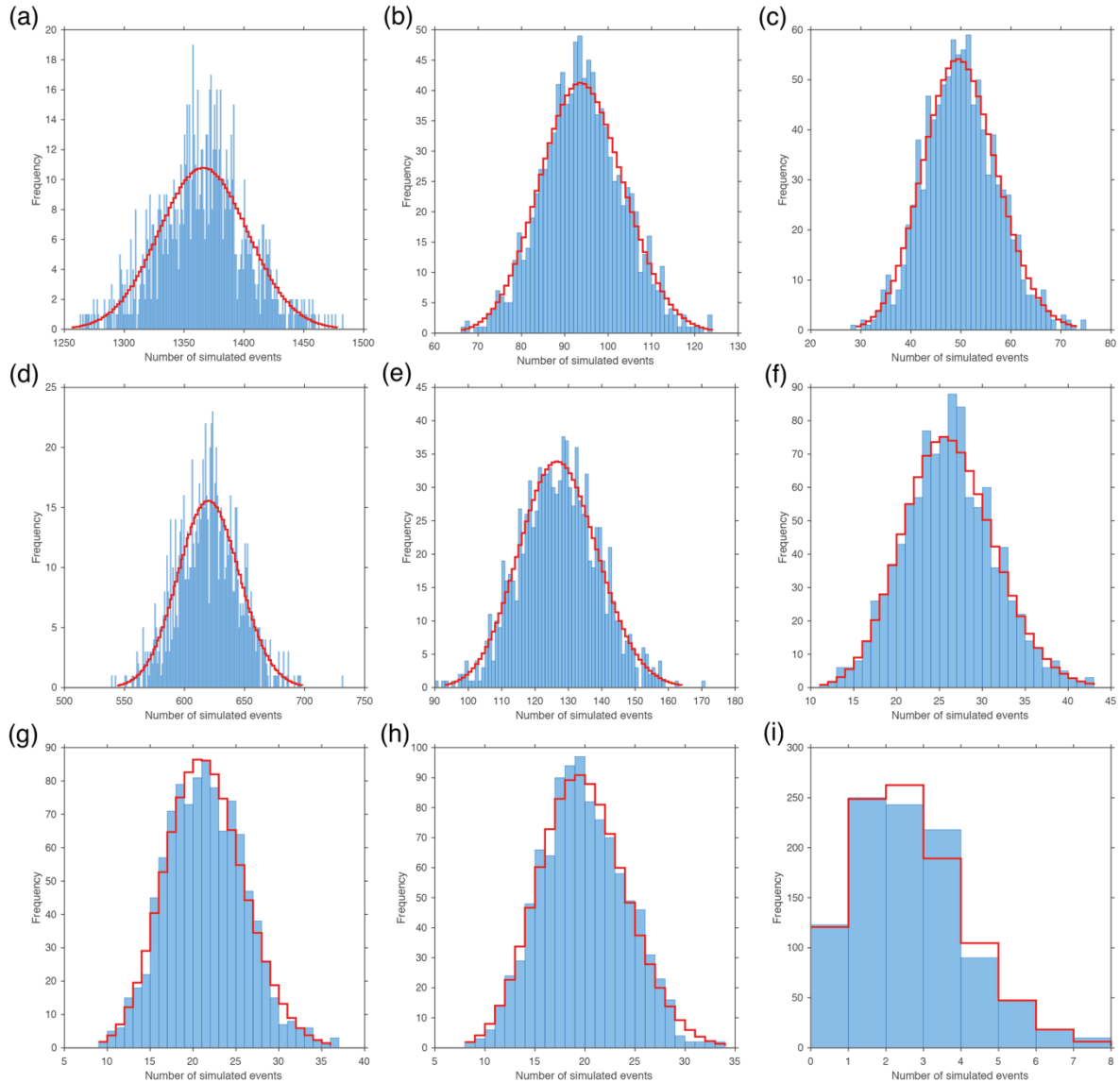
37 **Figure S2.** Simulation histograms at PNR-1z. Panels (a-i) show histograms from 9
 38 randomly selected forecast windows, each consisting of 1000 simulations of the number of
 39 simulated events over the forecast period. The red lines represent the fits of the negative
 40 binomial distributions to the histograms.

41

42

43

44



45

46 **Figure S3.** Simulation histograms at PNR-2. Panels (a-i) show histograms from 9
 47 randomly selected forecast windows, each consisting of 1000 simulations of the number of
 48 simulated events over the forecast period. The red lines represent the fits of the negative
 49 binomial distributions to the empirical histograms.

50

51

52

53

54 **Table S1.** Summary of the developed ETAS models.

Model	ETAS parameters	ETAS type	C_f	Update Frequency	Target magnitudes	Target catalog
ETAS1-global	Global ETAS	Standard	No	1 hour	$M \geq -1.5$	PNR-1z and 2
ETAS1-unoptimized	Optimized on PNR-1z	Standard	No	1 hour	$M \geq -1.5$	PNR-2 only
ETAS1-optimized	Optimized on specific catalog	Standard	No	1 hour	$M \geq -1.5$	PNR-1z and 2
ETAS2-unoptimized	Optimized on PNR-1z	Modified	PNR-1z bulk	1 hour	$M \geq -1.5$	PNR-2 only
ETAS2-bulk	Optimized on specific catalog	Modified	Bulk	1 hour	$M \geq -1.5$	PNR-1z and 2
ETAS2-specific	Optimized on specific catalog	Modified	Sleeve-specific	1 hour	$M \geq -1.5$	PNR-1z and 2

55

56 **Table S2.** ETAS parameters. When estimating the ETAS parameters, we constrain the
 57 branching ratio (*i.e.* the fraction of triggered events) to be less than 1.

58

Parameter	ETAS1-optimized		ETAS2-bulk		Global parameters
	PNR-1z	PNR-2	PNR-1z	PNR-2	
μ (eq/day)	0.26	0.31	N/A	N/A	0.26
c_f	N/A	N/A	0.29	1.70	N/A
c (days)	0.58	0.47	0.51	0.5	0.03
p	1.51	1.49	1.52	1.50	1.21
K	0.77	0.79	0.85	0.65	0.04
α	0.66	0.59	0.45	0.56	2.3

59

60 **Table S3.** Constants of proportionality (c_f) between injection rate and seismicity rate at
 61 PNR-1z sleeves.

62

		Sleeve number													
		#1	#2	#3	#12	#13	#14	#18 mini	#22a	#22b	#22c	#30a	#30b	#31	
c_f		1.35	0.24	0.42	0.17	0.13	0.04	0.25	0.54	0.75	0.001	1.96	2.48	0.22	
		Sleeve number												Bulk	
		#32	#39 mini	#41 mini	#37 mini	#40 mini	#38 mini	#35 mini	#37a	#37b	#38	#39	#40	#41	
c_f		0.28	0.08	1.42	0.001	0.43	0.52	0.21	0.66	0.39	1.28	1.23	1.40	0.30	0.29

63

64

65 **Table S4.** Constants of proportionality (c_f) between injection rate and seismicity rate at
 66 PNR-2 sleeves.

67

		Sleeve number								Bulk		
		#1a	#1b	#2	#3	#4	#5	#6a	#6b	#7		
c_f		0.71	4.38	3.39	2.93	1.66	0.73	0.65	1.42	0.70	1.70	

68