

A Deep Earthquake Catalog for Oklahoma and Southern Kansas Reveals Extensive Basement Fault Networks

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Abstract

The successful application of deep learning for seismic phase arrival time picking has increased the efficacy of earthquake catalog development workflows. Earthquake catalogs with lower magnitude of completeness and better locational precision than current standard practice can now be generated with very limited need for human review and without the need for earthquake templates, which are not always available. Here, we report on a ‘Deep Earthquake Catalog’ with over 300,000 events from a geographically extensive region spanning Oklahoma and Southern Kansas from January 2010 to December 2020 developed using a workflow that leverages deep learning for phase picking. The increased number of events and improved spatial resolution compared to the previous statewide catalogs reveals numerous discrete faults and both broad trends and localized patterns of seismicity. This rich dataset provides new opportunities for data-driven analyses of induced earthquakes.

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2 **Southern Kansas Reveals Extensive Basement Fault**
3 **Networks**

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6 **Key Points:**

- 7 • We report on a deep earthquake catalog of over 300,000 precisely located earth-
8 quakes.
- 9 • Numerous fault structures are revealed at high-resolution.
- 10 • The rich dataset provides new opportunities for data-driven analyses of induced
11 earthquakes.

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Abstract

The successful application of deep learning for seismic phase arrival time picking has increased the efficacy of earthquake catalog development workflows. Earthquake catalogs with lower magnitude of completeness and better locational precision than current standard practice can now be generated with very limited need for human review and without the need for earthquake templates, which are not always available. Here, we report on a ‘Deep Earthquake Catalog’ with over 300,000 events from a geographically extensive region spanning Oklahoma and Southern Kansas from January 2010 to December 2020 developed using a workflow that leverages deep learning for phase picking. The increased number of events and improved spatial resolution compared to the previous statewide catalogs reveals numerous discrete faults and both broad trends and localized patterns of seismicity. This rich dataset provides new opportunities for data-driven analyses of induced earthquakes.

Plain Language Summary

Oklahoma and Southern Kansas have experienced unprecedented rates of seismicity for over a decade as a result of unconventional hydrocarbon development. The region did not have a history of frequent earthquake activity, and little was known about the location or nature of the faults that came to host this seismicity. We reanalyzed the seismological data from January 2010 to December 2020 using an advanced workflow and produced a map of over 300,000 earthquakes, most of which were previously unknown. These earthquakes clearly illuminate the hidden fault structures throughout the region and can be used to better understand the regional seismicity.

1 Introduction

The workflow for developing an earthquake catalog with lower magnitude of completeness and increased location precision, i.e., a high-resolution earthquake catalog, compared to standard procedures has become faster and easier through the application of deep learning (DL) for seismic phase arrival time picking (Zhu & Beroza, 2019). The workflow (referred to as DL-assisted workflow hereafter) has been successfully used to efficiently create high-resolution earthquake catalogs (referred to as deep earthquake catalogs hereafter) in both anthropogenic (Park et al., 2020) and tectonic (Liu et al., 2020; Tan et al., 2021) settings. These studies demonstrate that we can now produce a cat-

alog with resolution and sensitivity approaching that of template matching, but without the need for the prior information in the form of a set of templates.

One of the clearest use cases of high-resolution earthquake catalogs is to map hidden fault structures and derive fault attributes such as orientations and dimensions (Schoenball & Ellsworth, 2017a; Skoumal et al., 2019). The resulting information can be used for geomechanical analysis, for example, to evaluate how likely faults are to slip (Walsh III & Zoback, 2016), to resolve fault plane ambiguities in focal mechanism solutions and to constrain local stress fields (Angelier, 1979), or to create fault models in numerical simulations (Yehya et al., 2018). This is especially useful for Oklahoma and Southern Kansas as almost all earthquakes have occurred on previously unmapped faults (Schoenball & Ellsworth, 2017b).

Previous studies improved the statewide earthquake catalog developed by the Oklahoma Geological Survey (OGS) (Walter et al., 2020) by precisely relocating earthquakes using a well-established workflow (Schoenball & Ellsworth, 2017b, 2017a) and by detecting and locating more events with template matching (Skoumal et al., 2019). These studies identified fault structures based on the epicentral distance among earthquake events, but the difference in spatial resolution and earthquake location methods led to some disagreements between the two results.

In this study, we use a DL-assisted workflow to process continuous waveform data in Oklahoma and Southern Kansas from January 2010 to December 2020 and report on a deep earthquake catalog with over 300,000 earthquakes that illuminates regional fault structures at both a broader scale and in more detail than previous catalogs. We show that the template-independency of the DL-assisted workflow can lead to earthquake catalogs with greater spatial resolution than template matching.

2 Earthquake Catalog Development

We used data from 17 publicly available seismic networks (codes 4H, 9L, GS, N4, NP, NQ, NX, O2, OK, TA, US, XR, Y7, Y9, ZD, ZP, and ZQ), comprising 422 stations. The geographic distribution of stations is shown in Figure 1 and the operational time of each station is shown in the supporting information (Figure S1).

We used a pre-trained neural network (Zhu & Beroza, 2019) to detect earthquakes and pick P- and S-phase arrival times. Because the picks and the prediction scores vary

74 depending on where the arrival is in the 30-second input window, we used a small stride
 75 of 2 seconds and used the picks that were consistently predicted in at least 5 windows
 76 with a prediction score of 0.5 or greater. These picks were then associated using a grid
 77 search algorithm similar to (Johnson et al., 1997; Zhang et al., 2019) where theoretical
 78 travel times were computed from the velocity model developed by OGS (Darold et al.,
 79 2015). We used the theoretical travel times to constrain further the possible time win-
 80 dow ranges between a pair of phases. This allows us to restrict the length of the time
 81 window between the first phase pick and the following phase picks during association,
 82 which removes potential ambiguities that can be introduced with longer time windows.
 83 To address seismic network variability, we used an adaptive association score as an event
 84 criterion, defined as

$$\text{Association score} = \frac{\sum_{i=1}^N w(r_i) \mathbf{1}\{\phi_i \in \mathcal{A}\}}{\sum_{i=1}^N w(r_i)} \quad (1)$$

85 which avoids thresholding on some constant number of required stations and/or phases.
 86 Here, N is the maximum number of phases that can be observed, i.e., twice the num-
 87 ber of the stations that were operating at the time of the event, and $w(r_i)$ is a weight-
 88 ing function. The indicator in the numerator (1) evaluates to 1 if the i 'th phase (ϕ_i) is
 89 in the association result (\mathcal{A}). To downweight stations more distant from the epicenter
 90 of the grid search solution, we used the weighting function:

$$w(r_i) = \min\left(\frac{1}{r_i}, \frac{1}{R}\right) \quad (2)$$

91 where we set the cutoff radius (R) for constant weight to 10 *km*. We required the as-
 92 sociation results to have an association score of 0.3 or greater and to have phase picks
 93 from at least 3 stations where 2 of them have both P- and S-phases picked. This is a bare
 94 minimum requirement to create an overdetermined system while resolving any phase con-
 95 fusion by the picking algorithm, i.e., mis-identifying a P-phase as an S-phase or vice versa.
 96 We determined initial hypocentral locations with HypoInverse (Klein, 2002) and refined
 97 them with HypoDD (Waldhauser & Ellsworth, 2000). For the final locations, we used
 98 the differential travel times calculated from the phase picks supplemented with cross-
 99 correlation measurements. For the latter, we followed the approach described in (Shelly
 100 et al., 2013, 2016) and used the three-point quadratic interpolation for subsample pre-
 101 cision and a weighting function that considers both the largest and the second largest
 102 cross-correlation coefficients to capture confidence in the measurements. We determined
 103 local magnitudes using the procedure and distance correction function reported in (Walter

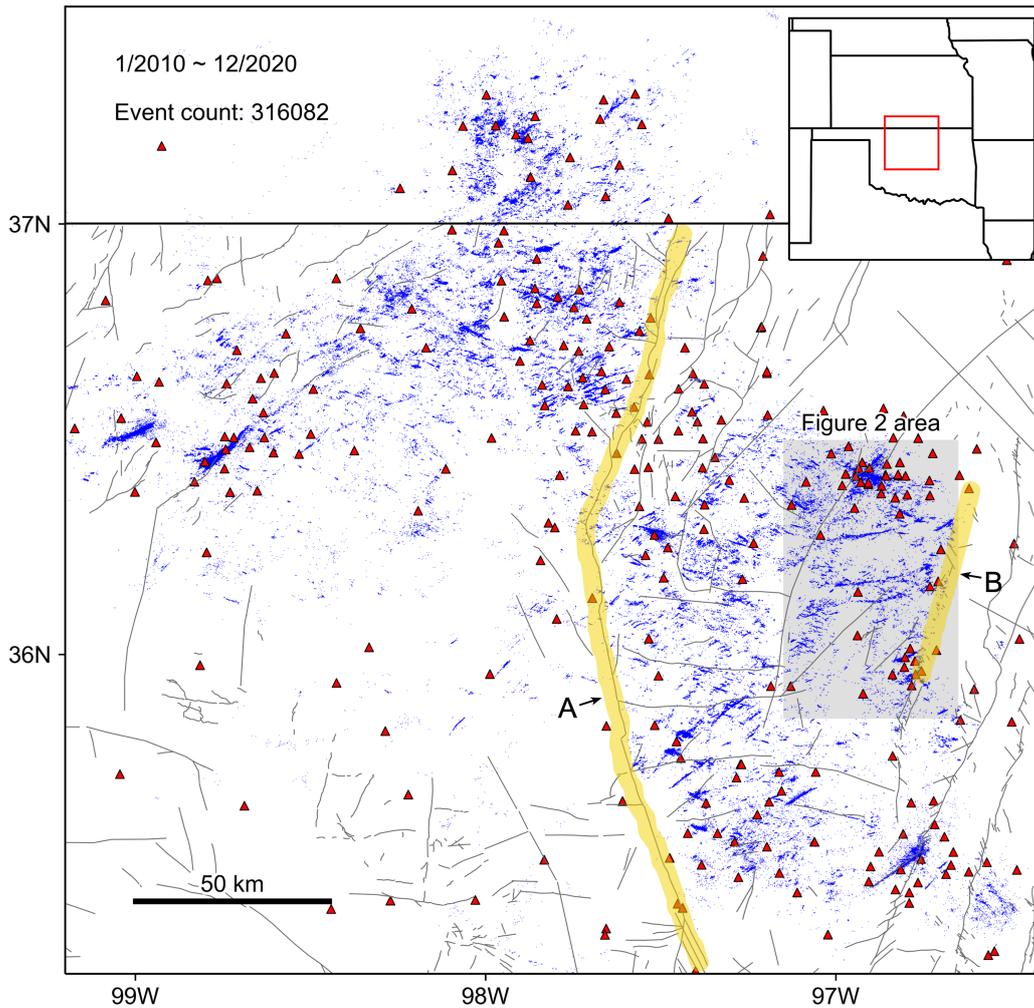


Figure 1. Map of the study area showing the faults compiled by OGS (Marsh & Holland, 2016) in black lines, seismic stations in red triangles, and epicenters of the events in our catalog in blue dots. The highlighted lines mark apparent seismicity boundaries. The area for Figure 2 is shown in grey box.

104 et al., 2020) but adopted moment magnitudes produced by St. Louis University (Herrmann
 105 et al., 2011) when available.

106 **3 Results**

107 **3.1 Regional map of earthquakes**

108 Figure 1 shows the epicenters in our catalog and the mapped faults compiled by
 109 OGS (Marsh & Holland, 2016). Equivalent maps with the events in other catalogs (Guy

110 et al., 2015; Schoenball & Ellsworth, 2017b; Skoumal et al., 2019) and the magnitude-
111 frequency distributions of the catalogs are shown in the supporting information (Figures
112 S2 through S6). A high-resolution map of the events colored by their origin time is at-
113 tached as a separate file (Figure S8). As noted previously, most of the earthquakes are
114 not associated with mapped faults (Schoenball & Ellsworth, 2017b). Instead, the event
115 epicenters define hundreds or even thousands of discrete fault structures, as seen here
116 in high spatial resolution. Note that the fault data were produced in 2016 and some of
117 the faults were defined by the earthquakes that had occurred on those faults by that time.
118 The fault that hosted the 2011 M5.6 Prague earthquake is an example.

119 One aspect that emerges in our catalog are clear boundaries of seismicity. The Nemaha
120 Ridge, which is highlighted and marked with A in Figure 1, has been hypothesized as
121 a barrier to flow (Weingarten et al., 2015) and our result strengthens the case. Specif-
122 ically, the seismicity in eastern Oklahoma tends to be constrained to the east of the ridge
123 south of 36.25 N, but to the west of the ridge farther north. Another example is marked
124 with B in Figure 1 where the seismicity is confined to the west of the highlighted line.
125 The origin of this boundary is not clear; however, we suspect that it too is geologically
126 controlled since there are mapped faults with similar orientations in the vicinity of line
127 B.

128 **3.2 Comparing the earthquake catalogs**

129 Figure 2 compares event epicenters between January 2010 and December 2016 in
130 the area highlighted in Figure 1 from our study with the two previous statewide cata-
131 logs (Schoenball & Ellsworth, 2017b; Skoumal et al., 2019). We refer the catalog from
132 Schoenball and Ellsworth (Schoenball & Ellsworth, 2017b) as SNE2017, and that from
133 Skoumal and coworkers (Skoumal et al., 2019) as SEA2019 hereafter. The epicenters be-
134 longing to the clustered structures in SNE2017, which were identified in a separate study
135 (Schoenball & Ellsworth, 2017a), are shown in different colors. The faults that were iden-
136 tified and fit in SEA2019 are plotted beneath the event epicenters. The spatial resolu-
137 tion of SNE2017 and SEA2019 limited the structures that can be confidently identified.
138 The number of events is larger in SEA2019 compared to SNE2017, but they are more
139 tightly clustered, which resulted in many small-scale structures. Our deep earthquake
140 catalog reveals that most of these separated structures are actually located within more
141 extensive and continuous structures.

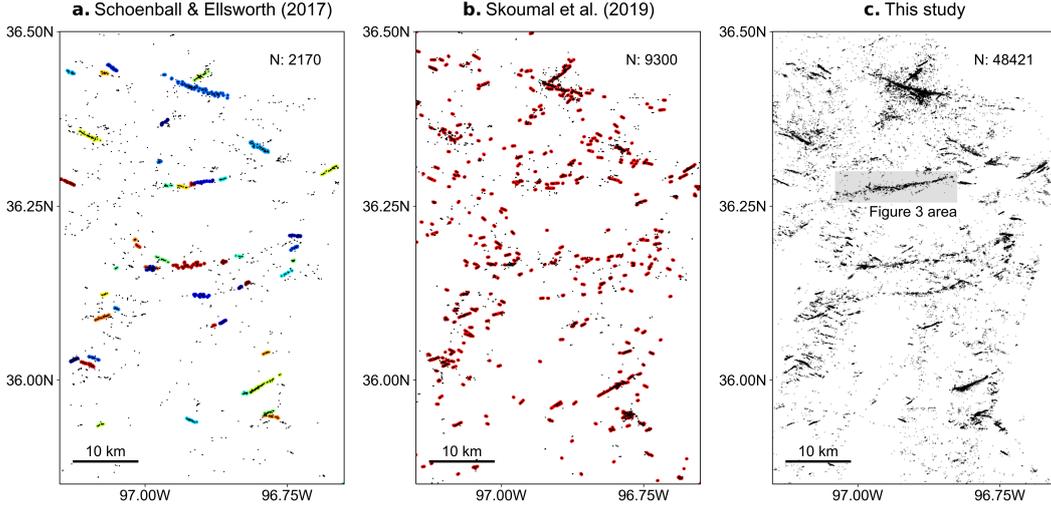


Figure 2. Comparisons of the event epicenters (black dots) among the three catalogs in the area highlighted in Figure 1. Events up to December 2016 are shown in **c** to match the date range with the other two catalogs. Events that were assigned to the identified fault structures in **a** are highlighted with colored backgrounds and the identified faults in **b** are plotted beneath the events in red. The area for Figure 3 in shown in **c**.

142 The spatial distribution of earthquakes seems more similar between SNE2017 and
 143 our study than SNE2017 and SEA2019. Note that SNE2017 was produced by relocat-
 144 ing the events from a routine catalog without increasing the event count while both SEA2019
 145 and this study increased the number of earthquakes detected to help resolve active struc-
 146 tures. To compare the distribution of locations quantitatively we used the Chamfer Dis-
 147 tance (CD), which in this context is defined as

$$CD(X, Y) = \frac{1}{N_x} \sum_{x \in X} \min_{y \in Y} \|x - y\|_2^2 + \frac{1}{N_y} \sum_{y \in Y} \min_{x \in X} \|y - x\|_2^2 \quad (3)$$

148 where x is each event epicenter in catalog X , y is each event epicenter in catalog Y , and
 149 N_x and N_y are event counts in catalog X and Y , respectively. While the absolute size
 150 of this distance does not convey much meaning, we can make relative comparisons among
 151 distances as smaller distances translate to higher similarity. When comparing a low-resolution
 152 catalog with a high-resolution catalog, the distance should decrease with increasing res-
 153 olution of the high-resolution catalog because ‘resolving’ in this context refers to resolv-
 154 ing the same underlying structures. Figure S7 gives more details on this logic. Using the
 155 events shown in Figure 2, the CD between SNE2017 and SEA2019, SNE2017 and our
 156 catalog, and SEA2019 and our catalog were 0.86, 0.54, and 0.66, respectively. The fact

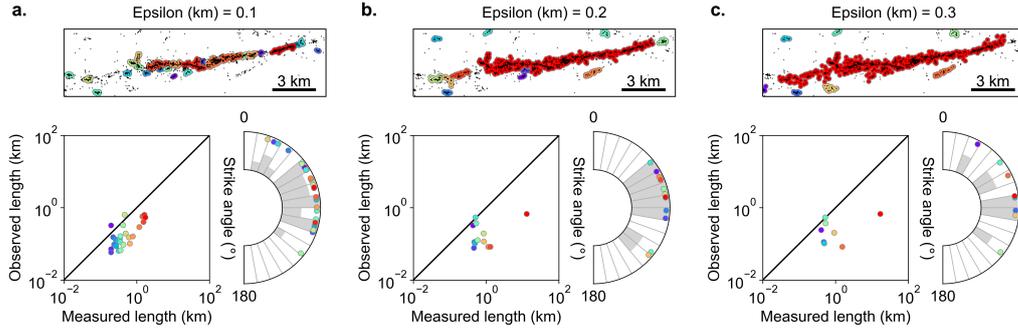


Figure 3. Clustering results of the earthquake events (up to December 2020) within the highlighted area in Figure 2-c. Events with the same background color belong to the same identified structure in the first row. The second row shows the distributions of measured lengths and strike angles of the identified structures. The lengths are plotted against the observed lengths, which are derived from the circular fault model (Eshelby, 1957) using the largest magnitude in each structure. Normalized histograms of the strike angles are shown in grey bars with a bin size of 10 degrees. The colors of the identified structures and the data points match in each column.

157 that the CDs between ours and each of the two previous catalogs are lower than the CD
 158 between the two previous catalogs indicates that the events that were added in our cat-
 159 alog resolved structures common to both, but previously less well illuminated. It is in-
 160 teresting to note that the CD between ours and SNE2017 was lower than the CD between
 161 ours and SEA2019 even though SEA2019 had over 4 times more events than SNE2017.
 162 This means that the additional events included in SEA2019 did not necessarily resolve
 163 the same underlying structures in SNE2017.

164 3.3 Identifying the structures

165 The increased spatial resolution of earthquake events in our catalog poses a chal-
 166 lenge when defining faults from earthquake locations. Some earthquakes form distinc-
 167 tive clusters that make the task easy, but it becomes less obvious for other earthquakes
 168 like those inside the highlighted box in Figure 2-c. Previous studies defined multiple struc-
 169 tures from these earthquakes (Figure 2-a and b), but one could possibly group all the
 170 earthquakes to form a linear trend in the box as a single structure when using our dataset
 171 (Figure 2-c).

172 To evaluate this quantitatively, we ran the DBSCAN algorithm (Ester et al., 1996)
173 on the event epicenters as was done in the previous studies. Figure 3 shows the cluster-
174 ing result under three different epsilon parameters, which control the distance cutoff used
175 to determine the neighboring events of each event. We used a fixed value of 3 for the pa-
176 rameter that controls the minimum number of neighbors while clustering. After cluster-
177 ing, we selected the clusters with aspect ratio of equal or greater than 3 and derived the
178 length of each structure by calculating the greatest distance between any two points within
179 the structure and the orientation using the largest eigenvector of the points within the
180 structure. The orientations were measured in strike angles, i.e., the angle from north in
181 the clockwise direction. For the lengths, we used the circular fault model (Eshelby, 1957)
182 to roughly translate the largest magnitude in each cluster into a corresponding length
183 scale. We used a constant stress drop value of 3 MPa, following (Huang et al., 2016), and
184 defined twice the radius as the observed length.

185 With the lowest epsilon value among the three, the earthquakes were grouped into
186 multiple small-scale structures, and the measured structure lengths followed the trend
187 of the observed lengths (Figure 3-a). With increasing epsilon, however, separated groups
188 began to merge, and the measured lengths became much larger than the observed lengths
189 (Figure 3-b, c). The distribution of strike angles also varied under different epsilon val-
190 ues. The data occupied more than half of the angle bins when epsilon was 0.1 km while
191 macroscopically, the events seem to form a structure with a strike angle close to 90 de-
192 grees as shown in the results with epsilon of 0.2 and 0.3 km.

193 4 Discussion

194 The catalog we developed using the DL-assisted workflow resulted in significantly
195 more events with high precision locations than the statewide template matching cata-
196 log (SEA2019), enabling the mapping of numerous fault structures only hinted at by both
197 SNE2017 and SEA2019. Our workflow, which requires no prior knowledge of template
198 events, was an important factor behind this increase. Because template matching requires
199 template events, which are only available for some stations, the SEA2019 study was un-
200 able to use all the waveform data available in the public domain at the time of their study.
201 This template-independency also allows us to apply the workflow in real-time to increase
202 the resolution over that of a conventionally developed earthquake catalog. Precision of
203 the earthquake hypocenters can be managed using the near real-time double-difference

204 approach (Waldhauser, 2009) and the neural network for picking phase arrivals can in-
205 crementally be trained for even better performance as we collect more labeled data (Chai
206 et al., 2020).

207 The catalog illuminates previously hidden fault structures in Oklahoma and South-
208 ern Kansas and can be used to derive fault attributes such as dimensions and orienta-
209 tions for further analysis. However, we showed that a simple clustering algorithm such
210 as DBSCAN that is purely based on earthquake locations has limitations and the statis-
211 tics of the identified faults derived from it can be very sensitive to the parameters. Fu-
212 ture work is needed on algorithms for identifying the faults from seismicity distributions.
213 These algorithms should be robust against missing events and changes in relative event
214 locations. Using a probabilistic approach such as sampling the events before clustering
215 and quantifying the uncertainties of the derived fault attributes is another option.

216 5 Conclusion

217 Developing a high-resolution earthquake catalog has become faster and easier due
218 to the application of deep learning algorithms for seismic phase arrival time picking. Through
219 our case study of a decade of Oklahoma and Southern Kansas seismicity, we found this
220 workflow provides significant improvements over the existing catalogs. The newly iden-
221 tified seismicity illuminates numerous previously unseen fault structures and sharpens
222 the definition of those previously revealed.

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227 The links to each seismic network data are 4H: <https://doi.org/10.7914/SN/4H.2014>,
228 9L: <https://doi.org/10.7914/SN/9L.2013>, GS: <https://doi.org/10.7914/SN/GS>,
229 N4: <https://doi.org/10.7914/SN/N4>, NP: <https://doi.org/10.7914/SN/NP>, NQ:
230 <https://doi.org/10.7914/SN/NQ>, NX: <https://doi.org/10.7914/SN/NX>, O2: <https://doi.org/10.7914/SN/O2>, OK: <https://doi.org/10.7914/SN/OK>, TA: <https://doi.org/10.7914/SN/TA>, US: <https://doi.org/10.7914/SN/US>, XR: <https://doi.org/10.7914/SN/XR.2016>, Y7: <https://doi.org/10.7914/SN/Y7.2016>, Y9: <https://doi.org/10.7914/SN/Y9.2016>, ZD: <https://doi.org/10.7914/SN/ZD.2014>, ZP: <https://doi.org/10.7914/SN/ZP.2014>.

235 doi.org/10.7914/SN/ZP.2016, and ZQ: <https://doi.org/10.7914/SN/ZQ.2011>. The
 236 earthquake catalog produced from this study is included in the supporting information
 237 (Table S1).

238 References

- 239 Angelier, J. (1979). Determination of the mean principal directions of stresses for a
 240 given fault population. *Tectonophysics*, *56*(3-4), T17–T26.
- 241 Chai, C., Maceira, M., Santos-Villalobos, H. J., Venkatakrisnan, S. V., Schoenball,
 242 M., Zhu, W., . . . Team, E. C. (2020). Using a deep neural network and trans-
 243 fer learning to bridge scales for seismic phase picking. *Geophysical Research*
 244 *Letters*, *47*(16), e2020GL088651.
- 245 Darold, A. P., Holland, A. A., Morris, J. K., & Gibson, A. R. (2015). Oklahoma
 246 earthquake summary report 2014. *Okla. Geol. Surv. Open-File Rept. OF1-*
 247 *2015*, 1–46.
- 248 Eshelby, J. D. (1957). The determination of the elastic field of an ellipsoidal inclu-
 249 sion, and related problems. *Proceedings of the royal society of London. Series*
 250 *A. Mathematical and physical sciences*, *241*(1226), 376–396.
- 251 Ester, M., Kriegel, H.-P., Sander, J., Xu, X., et al. (1996). A density-based algo-
 252 rithm for discovering clusters in large spatial databases with noise. In *kdd*
 253 (Vol. 96, pp. 226–231).
- 254 Guy, M. R., Patton, J. M., Fee, J., Hearne, M., Martinez, E. M., Ketchum, D. C.,
 255 . . . others (2015). *National earthquake information center systems overview*
 256 *and integration*. US Department of the Interior, US Geological Survey.
- 257 Herrmann, R. B., Benz, H., & Ammon, C. J. (2011). Monitoring the earthquake
 258 source process in north america. *Bulletin of the Seismological Society of Amer-*
 259 *ica*, *101*(6), 2609–2625.
- 260 Huang, Y., Beroza, G. C., & Ellsworth, W. L. (2016). Stress drop estimates of po-
 261 tentially induced earthquakes in the guy-greenbrier sequence. *Journal of Geo-*
 262 *physical Research: Solid Earth*, *121*(9), 6597–6607.
- 263 Johnson, C. E., Lindh, A., & Hirshorn, B. (1997). Robust regional phase associa-
 264 tion.
- 265 Klein, F. W. (2002). *User’s guide to hypoinverse-2000, a fortran program to solve*
 266 *for earthquake locations and magnitudes* (Tech. Rep.). US Geological Survey.

- 267 Liu, M., Zhang, M., Zhu, W., Ellsworth, W. L., & Li, H. (2020). Rapid charac-
 268 terization of the July 2019 ridgecrest, California, earthquake sequence from
 269 raw seismic data using machine-learning phase picker. *Geophysical Research*
 270 *Letters*, *47*(4), e2019GL086189.
- 271 Marsh, S., & Holland, A. (2016). Comprehensive fault database and interpretive
 272 fault map of Oklahoma. *Oklahoma Geol. Surv. Open-File Rep. OF2-2016, Okla-*
 273 *homa Geological Survey, Norman, OK.*
- 274 Park, Y., Mousavi, S. M., Zhu, W., Ellsworth, W. L., & Beroza, G. C. (2020).
 275 Machine-learning-based analysis of the Guy-Greenbrier, Arkansas earthquakes:
 276 A tale of two sequences. *Geophysical Research Letters*, *47*(6), e2020GL087032.
- 277 Schoenball, M., & Ellsworth, W. L. (2017a). A systematic assessment of the spa-
 278 tiotemporal evolution of fault activation through induced seismicity in Okla-
 279 homa and southern Kansas. *Journal of Geophysical Research: Solid Earth*,
 280 *122*(12), 10–189.
- 281 Schoenball, M., & Ellsworth, W. L. (2017b). Waveform-relocated earthquake catalog
 282 for Oklahoma and southern Kansas illuminates the regional fault network. *Seis-*
 283 *mological Research Letters*, *88*(5), 1252–1258.
- 284 Shelly, D. R., Ellsworth, W. L., & Hill, D. P. (2016). Fluid-faulting evolution in
 285 high definition: Connecting fault structure and frequency-magnitude variations
 286 during the 2014 Long Valley Caldera, California, earthquake swarm. *Journal of*
 287 *Geophysical Research: Solid Earth*, *121*(3), 1776–1795.
- 288 Shelly, D. R., Moran, S. C., & Thelen, W. A. (2013). Evidence for fluid-triggered
 289 slip in the 2009 Mount Rainier, Washington earthquake swarm. *Geophysical Re-*
 290 *search Letters*, *40*(8), 1506–1512.
- 291 Skoumal, R. J., Kaven, J. O., & Walter, J. I. (2019). Characterizing seismogenic
 292 fault structures in Oklahoma using a relocated template-matched catalog. *Seis-*
 293 *mological Research Letters*, *90*(4), 1535–1543.
- 294 Tan, Y. J., Waldhauser, F., Ellsworth, W. L., Zhang, M., Zhu, W., Michele, M., ...
 295 Segou, M. (2021). Machine-learning-based high-resolution earthquake cata-
 296 log reveals how complex fault structures were activated during the 2016–2017
 297 central Italy sequence. *The Seismic Record*, *1*(1), 11–19.
- 298 Waldhauser, F. (2009). Near-real-time double-difference event location using long-
 299 term seismic archives, with application to northern California. *Bulletin of the*

- 300 *Seismological Society of America*, 99(5), 2736–2748.
- 301 Waldhauser, F., & Ellsworth, W. L. (2000). A double-difference earthquake location
302 algorithm: Method and application to the northern hayward fault, california.
303 *Bulletin of the seismological society of America*, 90(6), 1353–1368.
- 304 Walsh III, F. R., & Zoback, M. D. (2016). Probabilistic assessment of potential
305 fault slip related to injection-induced earthquakes: Application to north-central
306 oklahoma, usa. *Geology*, 44(12), 991–994.
- 307 Walter, J. I., Ogwari, P., Thiel, A., Ferrer, F., Woelfel, I., Chang, J. C., . . . Holland,
308 A. A. (2020). The oklahoma geological survey statewide seismic network.
309 *Seismological Research Letters*, 91(2A), 611–621.
- 310 Weingarten, M., Ge, S., Godt, J. W., Bekins, B. A., & Rubinstein, J. L. (2015).
311 High-rate injection is associated with the increase in us mid-continent seismic-
312 ity. *Science*, 348(6241), 1336–1340.
- 313 Yehya, A., Yang, Z., & Rice, J. R. (2018). Effect of fault architecture and permeabil-
314 ity evolution on response to fluid injection. *Journal of Geophysical Research:*
315 *Solid Earth*, 123(11), 9982–9997.
- 316 Zhang, M., Ellsworth, W. L., & Beroza, G. C. (2019). Rapid earthquake association
317 and location. *Seismological Research Letters*, 90(6), 2276–2284.
- 318 Zhu, W., & Beroza, G. C. (2019). Phasenet: a deep-neural-network-based seismic
319 arrival-time picking method. *Geophysical Journal International*, 216(1), 261–
320 273.