Bursts of fast propagating swarms of induced earthquakes at the Groningen gas field

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Abstract

Gas extraction from the Groningen gas reservoir, located in northeastern Netherlands, has led to a drop in pressure driving compaction and induced seismicity. Stress-based models have shown success in forecasting induced seismicity in this particular context and elsewhere, but they generally assume that earthquake clustering is negligible. To assess earthquake clustering at Groningen, we generate an enhanced seismicity catalog using a deep-learning-based workflow. We identify and locate 1369 events between 2015 and 2022, including 660 newly detected events not previously identified by the standard catalog from the Royal Netherlands Meteorological Institute. Using the nearest-neighbor distance approach, we find that 72% of events are background independent events, while the remaining 28% belong to clusters. 55% of the clustered events are swarm-like, while the rest are aftershock-like. Among the swarms include five newly identified swarm sequences propagating at high velocities between 3 – 50 km/day along directions that do not follow mapped faults or existing structures and frequently exhibit a sharp turn in the middle of the sequence. The swarms occurred around the time of the maximum compaction rate between November 2016 and May 2017 in the Zechstein layer, above the anhydrite caprock, and well-above the directly induced earthquakes that occur within the reservoir and caprock. We suggest that these swarms are related to aseismic deformation within the salt formation rather than fluids. This study suggests that propagating swarms do not always signify fluid migration.

Introduction

Industrial activities, such as gas extraction, wastewater disposal, hydraulic stimulation, geothermal energy production, carbon dioxide sequestration, and water impoundment from dams can produce substantial stress changes in the Earth's crust that can induce seismicity (Ellsworth, 2013; Grigoli *et al.*, 2017; Keranen and Weingarten, 2018; Atkinson *et al.*, 2020; Wu *et al.*, 2022; Moein *et al.*, 2023). The induced earthquakes can occasionally reach magnitudes of 5 or above, with hypocenters that are often shallower than those of natural seismicity (Hough, 2015), making it capable of damaging nearby structures (Clayton *et al.*, 2016). Management of seismic risks to be within an acceptable level is critical for successful operations.

Induced earthquakes, which exclude background earthquakes driven by tectonics and other natural causes of stress changes, can generally be grouped into two modes based on their clustering behaviors. The first mode includes independent background events that are driven directly by the stress changes due to the large scale human activity, whether from changes in pore pressure as the fluid diffuses (Hubbert and Rubey, 1959; Nur and Booker, 1972) or long-range poroelastic stress changes (Segall, 1989; Segall *et al.*, 1994; Goebel *et al.*, 2017; Zhai *et al.*, 2019). These events are expected to follow a Poisson process, generally non-homogeneous, with time-varying rates governed by stress changes (Dempsey and Suckale, 2017; Dahm and Hainzl, 2022; Smith *et al.*, 2022; Acosta *et al.*, 2023). The second mode includes the clustered events that appear close in space and time with some independent events and often occur as aftershocks, or more occasionally as foreshocks as observed for natural seismicity as well (Ogata, 1988). Mechanistically, these events are triggered by stress changes imparted by a previous earthquake rather than the industrial operations. Aftershocks generally follow well-known patterns, including the decay of their occurrence rates with time as a power law (Omori, 1894; Utsu, 1961) and a scaling in which the largest aftershock is approximately 1.2 magnitude unit lower than the mainshock (Richter, 1958). Clustered events may occasionally deviate from this well-defined pattern and occur as enigmatic bursts of small-magnitude earthquakes without an identifiable mainshock, referred to as swarms (Mogi, 1963). They often exhibit migratory patterns (Audin *et al.*, 2002; Hainzl and Fischer, 2002; Chen and Shearer, 2011) and are a manifestation of underlying aseismic processes such as spontaneous slow slip events (Lohman and McGuire, 2007; Passarelli *et al.*, 2015; Gualandi *et al.*, 2017; Jiang *et al.*, 2022), fluid pressure diffusion (Shapiro *et al.*, 1997; Audin *et al.*, 2002; Hainzl and Fischer, 2002; Shelly *et al.*, 2013; Ruhl *et al.*, 2016; Ross and Cochran, 2021), or a complex interaction of both (Dublanchet and De Barros, 2021; Sirorattanakul *et al.*, 2022; Yukutake *et al.*, 2022). Clustering is generally small in induced seismicity with a proportion of clustered events generally less than 30% (Zaliapin and Ben-Zion, 2016; Cochran *et al.*, 2020; Karimi and Davidsen, 2023), while clusters typically represent up to 70% of natural seismicity (Zaliapin and Ben-Zion, 2013a). Swarms have also been observed in the context of induced seismicity where they are generally ascribed to fluid migration (Ake *et al.*, 2005; Baisch *et al.*, 2006; Albaric *et al.*, 2014; Kwiatek *et al.*, 2019).

In this study, we take advantage of publicly available seismic datasets related to seismicity induced by production in the Groningen gas field in the northeastern Netherlands (Dost *et al.*, 2017; Willacy *et al.*, 2019; Oates *et al.*, 2022) to investigate the degree of clustering and the possible mechanisms involved. We produce an enhanced seismicity catalog for the region using a deep-learning-based workflow. The improved catalog reveals many previously unidentified events, which enables more extensive statistical analysis of earthquake clusters. The newly detected events include five distinct swarm sequences propagating at high velocity between 3 – 50 km/day.

The Groningen gas field, overview of previous studies of induced seismicity

The Groningen gas field is the largest in Western Europe (Figure 1), with an initial gas reserve of approximately 2913 billion cubic meters (BCM) (Burkitov et al., 2016). The gas comprises 85% methane (CH4), 14% nitrogen (N2), and 1% carbon dioxide (CO2) (Stäuble and Milius, 1970; Burkitov *et al.*, 2016). The reservoir lies at a depth of between 2.6 and 3.2 km and spans approximately 35 km east-west and 50 km north-south as a part of the Upper Rotlingend Group composed of interbedded Slochteren sandstone and Ten Boer claystone units. Its thickness varies substantially from 90 m in the southeast to 300 m in the northwest. The coal layers in the underlying Pennsylvanian Carboniferous limestone are the source of the gas. The reservoir is sealed by an overlying thick and impermeable caprock of anhydrite and evaporite layers of the Permian Zechstein group, an aquifer toward the north, and a system of normal faults (de Jager and Visser, 2017). Because of the limited connection with the surrounding groundwater, gas extraction has led to significant pressure depletion from 34.68 MPa, close to hydrostatic pressure (Burkitov *et al.*, 2016), to < 10 MPa (Meyer *et al.*, 2023), which resulted in surface subsidence of almost 40 cm (Smith *et al.*, 2019).

While the field has been in production since 1963, induced seismicity did not start until 1991 (Dost *et al.*, 2017). From 1991 to 2013, the number of earthquakes increased exponentially, prompting significant efforts to deploy additional monitoring instruments. The first regional network in operation since 1995 consisted of eight stations, each with three-component geophones at four different depth levels (50 m, 100 m, 150 m, and 200 m) and a surface accelerometer. Several upgrades of the network followed. In a major upgrade late 2014, 59 additional stations were deployed, significantly improving seismic activity detection (Dost *et al.*, 2017). Most earthquakes align well with one of the > 1100 normal faults mapped by seismic techniques that offset the gas reservoir (Visser and Solano Viota, 2017) and are located primarily within the reservoir (Willacy et al., 2019) or in the overburden (Smith *et al.*, 2020). They are thought to be driven primarily by poroelastic stresses induced by bulk reservoir volume decrease (Bourne *et al.*, 2014; Dempsey and Suckale, 2017; Candela *et al.*, 2019; Smith *et al.*, 2022) or by stress concentration around faults offsetting the reservoir resulting from compaction (Bourne *et al.*, 2014; Buijze *et al.*, 2017; Van Wees *et al.*, 2018). The largest earthquake to date is the 2012 M_w 3.6 Huizinge earthquake, which sparked public concerns and prompted the regulators to request ramping down of production and to eventually shut it down long before exhaustion of the gas reserve (de Waal *et al.*, 2015; van Thienen-Visser and Breunese, 2015; Muntendam-Bos *et al.*, 2017).

In recent years, many researchers have developed computationally efficient models to forecast occurrence rates of induced seismicity based on stress changes from industrial operations (Segall and Lu, 2015; Bourne and Oates, 2017; Dempsey and Suckale, 2017; Bourne *et al.*, 2018; Langenbruch *et al.*, 2018; Candela *et al.*, 2019, 2022; Zhai *et al.*, 2019; Richter *et al.*, 2020; Dahm and Hainzl, 2022; Heimisson *et al.*, 2022; Kühn *et al.*, 2022; Smith *et al.*, 2022; Acosta *et al.*, 2023; Kim and Avouac, 2023). One major limitation of these stress-based models is that they do not account for interactions between earthquakes that may lead to secondary triggering and appear as clustered events. While induced earthquakes tend to have fewer clustered events than natural earthquakes, their proportions can be > 50% depending on the geological settings, which is non-negligible (Zaliapin and Ben-Zion, 2016). A better understanding of clustering behaviors of induced seismicity can lead to further improvements in these models.

Data and Methods

Enhanced seismicity catalog generation

The Royal Netherlands Meteorological Institute (KNMI) has been the authoritative governmental institution responsible for maintaining a seismicity catalog for the area surrounding the Groningen gas field since 1995. To supplement the KNMI catalog, we use a recently developed deep-learning-based workflow to build an enhanced high-resolution seismicity catalog between 2015 and 2022 covering the domain spanning latitude 53.05 – 53.50°N and longitude 6.48 – 7.05°E. As summarized below, the workflow consists of multiple steps, including phase picking, phase association, earthquake location, and magnitude estimation.

Waveform data from seismic stations in the NL and NR networks located within our domain are used in this analysis (Figure S1). We first apply the PhaseNet automated phase picking algorithm based on a convolutional neural network (Zhu and Beroza, 2019) to detect P- and S-wave arrivals. The algorithm accepts one- or three-component waveform data as input and outputs a list of timestamped P- or S-wave arrival times. We use the standard model included with the PhaseNet distribution, which was trained on California data based on manual picks from seismic analysts at the Northern California Earthquake Data Center but has been shown to effectively generalize to other regions worldwide, including Hawaii (Wilding *et al.*, 2023), Italy (Tan *et al.*, 2021), and Arkansas, USA (Park *et al.*, 2020). The initial iteration of the catalog, spanning from mid-2015 to 2018, includes picking from both surface and borehole seismometers. However, when we expand the catalog to include the first few months of 2015 and from 2019 to 2022, we only apply PhaseNet to surface sensors for computational efficiency. Additionally, for instruments with a sampling rate greater than 100 Hz, we decimate waveform data to 100 Hz per PhaseNet requirements. The output from PhaseNet also has probability labels between 0 and 1, indicating confidence in the pick. We set a probability threshold of 0.3 and remove picks below this confidence threshold.

The P and S arrival picks are then associated into discrete earthquake events using the Gaussian Mixture Model Associator, GaMMA (Zhu *et al.*, 2022). GaMMA probabilistically assigns clusters of P and S picks to individual sources based on identified hyperbolic moveouts and iterates those assignments using the expectation-maximization process. The main parameters controlling the association process are the maximum time ε between two picks to be considered as a neighbor of the other and the scalar P- and S-wave velocity used to backproject arrivals. Even though GaMMA uses a uniform velocity model, it can account for travel-time errors in back-projection due to three-dimensional variation of the velocity model by allowing large uncertainty in arrival times during the clustering stage. We test different parameters and identify the best set of parameters as those that include the greatest number of events previously identified by KNMI. The best combination of parameters uses ε of 3 seconds, a P-wave velocity of 3.0 km/s, and an S-wave velocity of 1.8 km/s. With this set of parameters, GaMMA identifies 709 out of 739 events in the KNMI catalog over the same spatial and temporal coverage. After the association, we filter out previously unidentified events with fewer than 5 P or S picks and are left with 2591 events. Finally, we manually inspect waveforms of all newly identified events and remove the spurious picks resulting in 1369 events, including 660 newly detected events (Figure S2 and S3).

The events are then located with a modified version of the Hypocenter inversion with Stein Variational Inference and physics-informed neural networks (HypoSVI) program (Smith *et al.*, 2021), adapted to allow for a 3-D velocity model. The velocity model of the Groningen region used in this study was produced by Nederlandse Aardolie Maatschappij (NAM) from seismic reflection, seismic refraction, sonic log and well core samples (Nederlandse Aardolie

Maatschappij, 2017). Since HypoSVI inverts for the full posterior distribution of an earthquake location, the algorithm also outputs associated location uncertainties. Compared with the KNMI catalog, we find approximately 40 mismatched events. Most of these events are located near the edges of the velocity model domain by both our algorithm and by KNMI. They are most likely affected by the low number of picks on stations within the velocity model domain and increased picking errors for arrivals with a lower signal-to-noise ratio. To maintain the integrity of the catalog, we manually assign the locations of these events to those provided by KNMI, which can be identified by their depth of exactly 3 km. The events that include the borehole picks can be distinguished by event ID numbers that begin with "100" in contrast to other events that only have picks on surface geophones. Events with picks only from the surface geophones have larger depth uncertainty, as evidenced by several surface-sensor-only events with depths far from the reservoir. These depths can be considered artifacts of the data downsampling process. We have also compared the epicentral (horizontal) locations derived using picks from all sensors and only from surface sensors. They are largely unaffected by excluding the picks from the borehole sensors.

Local earthquake magnitudes (M_L) are calculated with the same procedure used by KNMI (NORSAR, 2018), which can be calculated by using the following equation:

$$M_L = \log_{10} A + 1.33 \log_{10} R + 0.00139R + 0.424 \quad (1)$$

where A is amplitude measurement in mm on a simulated Wood-Anderson seismometer of the deepest available borehole sensor for a given station, and R is the source-receiver distance in km. The amplitudes are measured as the peak signal amplitude of the waveform (absolute value). While it is possible to convert local magnitude to moment magnitude using the relation derived by Dost *et al.* (2018), we restrict our analysis to local magnitude.

Clustering analysis

To analyze the clustering behaviors of seismicity in the Groningen gas field, we apply the nearest-neighbor distance approach (Zaliapin and Ben-Zion, 2013a, 2013b) to the enhanced seismicity catalog. We consider only events located within the boundary of the Groningen gas field that are larger than the completeness magnitude (M_c) of 0.5. For each event j in the catalog, we search for the preceding event i that is most likely to be the parent (mainshock) of event j. The proximity distance between any event pair (i, j) can be quantified using a space-time-magnitude metric normalized by the magnitude of the parent event (Baiesi and Paczuski, 2004; Zaliapin *et al.*, 2008) defined as follows:

$$\eta_{ij} = t_{ij}\left(r_{ij}\right)^{d_f} 10^{-b(m_i - M_c)} \tag{2}$$

where $t_{ij} = t_j - t_i$ is the time between the event pair, r_{ij} is the distance between the epicenters of the event pair, d_f is the fractal dimension of earthquake epicenters taken to be 1.6 (Zaliapin and Ben-Zion, 2013a), b is the Gutenberg-Richter b-value of the frequency-magnitude distribution, and m_i is the magnitude of event i. Since depth uncertainty is large, we do not include depths in the proximity distance calculations.

For each event j, the event i^* with the smallest proximity distance η_{ij} is the nearest neighbor and hence most likely to be the parent of event j. The results can be expanded to two dimensions as rescaled time T_j and rescaled distance R_j, defined as follows (Zaliapin and Ben-Zion, 2013a):

$$T_j = t_{i^*j} 10^{-\frac{b}{2}(m_{i^*} - M_c)} \tag{3}$$

$$R_j = \left(r_{i^*j}\right)^{d_f} 10^{-\frac{b}{2}(m_{i^*} - M_c)}$$

The distribution of nearest-neighbor distance η_j is expected to be bimodal. The first mode is the independent events represented by a time-stationary, space-inhomogeneous Poisson process concentrating along $\log_{10} T_j + \log_{10} R_j =$ constant. The second mode is the clustered events with considerably smaller T_j and R_j, constituting foreshock-mainshock-aftershock sequences and swarms (Zaliapin *et al.*, 2008; Zaliapin and Ben-Zion, 2013a). The separation between the two modes can be approximated by a 1-D Gaussian mixture model applied on η_j (Hicks, 2011) using Matlab *fitgmdist* function. The mode separator η_0 is chosen to be where the probability density function of the two modes intersects. We consider events with $\eta_j \geq \eta_0$ to be independent events and $\eta_j < \eta_0$ to be clustered events (Zaliapin and Ben-Zion, 2013a).

The nearest-neighbor distance approach was originally analyzed for an epidemic-type aftershock sequence (ETAS) model (Ogata, 1988) with an assumption that the background independent events follow a time-stationary, space-inhomogeneous Poisson process (Zaliapin *et al.*, 2008). In the case of induced seismicity, we expect the background Poisson rates of independent events to be inhomogeneous in time as modulated by injection or extraction rates. To test a posteriori the effectiveness of the nearest-neighbor distance approach for induced seismicity and the robustness of the estimated mode separator η_0, we take events with $\eta_j \geq \eta_0$, create 100 shuffled catalogs by randomly permuting the order of the magnitudes and locations, and calculate nearest-neighbor distances for events in these shuffled catalogs, similar to those done in Karimi and Davidsen (2023). Since the shuffling removes any clusters while preserving the seismicity rate and spatial distribution, the distribution of nearest-neighbor distances of these shuffled events reflects the true distribution of the independent mode and hence the majority of events should have $\eta_{j,\text{shuffled}} \geq \eta_0$

if the chosen η_0 is appropriate. Unlike in Karimi and Davidsen (2023), by shuffling only events with $\eta_j \geq \eta_0$, we reduce bias of the clustered events on the temporal rate of independent events. In principle, we can also completely remove the time clustering by sampling new times from a uniform distribution (Zaliapin and Ben-Zion, 2020) but then we would also remove any time-inhomogeneous nature of the independent events.

Furthermore, we also evaluate the relative variability of the interevent times distribution using the coefficient of variation (CoV), defined as the ratio of its standard deviation and its mean. Random process (Poissonian) is expected to have CoV in order of unity. Larger CoV suggests the presence of clustering, while smaller CoV suggests a periodic behavior. For a given η_0, the CoV can be used to evaluate whether the independent events are Poissonian. If the chosen η_0 is too small, events with $\eta_j \geq \eta_0$ would include some clustered events and hence the CoV would become significantly greater than one. In contrary to the shuffling analysis which evaluates the upper bound of the appropriate η_0, the CoV evaluates its lower bound.

We additionally use the Schuster spectrum method (Ader and Avouac, 2013) to verify that, once clustered events are removed based on the chosen value of the mode separator η_0, the remaining events are consistence with a non-homogeneous Poisson process. The method is based on the Schuster tests (Schuster, 1897), which evaluates the amount of seismicity rate variation for a given periodicity. By calculating the Schuster p-value for different periods, we construct a Schuster spectrum and compare with the expectation for a Poisson process. This procedure aids in verification of the quality of the declustering.

To further study the relationship between events, we create a spanning tree by connecting each event to its most likely parent. The strength of each link is inversely proportional to the nearest-neighbor distance η_j. By removing weak links with $\eta_j \geq \eta_0$, we create a spanning forest consisting of single-event trees with no links and other multievent clusters (Zaliapin and Ben-Zion, 2013a). The independent events previously identified include the singles and the first event from each cluster. We can calculate the average leaf depth for each cluster by averaging the number of links needed to connect events without children to the first event or the root (Zaliapin and Ben-Zion, 2013b). Swarm-like sequences have large average leaf depth, while foreshock-mainshock-aftershock sequences have small average leaf depth.

Results

Catalog overall properties

Compared to the standard catalog from the Royal Netherlands Meteorological Institute (KNMI), our deep-learning-based workflow enables us to increase the number of detected events between 2015 and 2022 from 739 to 1369. 709 events from the KNMI catalog were identified by our workflow, leaving only 30 events unidentified by our method. 1297 events are located within the horizontal extent of the gas field, which we use for the analysis hereafter.

Despite being automatically generated products, our events display good agreement in both locations and magnitudes with the KNMI catalog (Figure S4). The horizontal location differences for events with $M_L \geq 0.5$ are less than 675 m on average. Most events with large location differences are either located near the edge of the available velocity model or small magnitude events where arrival picks have large uncertainty. The magnitude differences are less than 0.1 magnitude unit on average. Only 78 events (12%) have magnitude differences greater than 0.2 magnitude units. There is one M3 event that is presented in our catalog but not in the KNMI catalog. Since that event is located close the edge of the velocity model, the arrival picks may have large uncertainty and bias its location, and therefore, its magnitude. Our catalog also reports depth rather than a fixed depth of 3 km, as the KNMI catalog does. In comparison to the catalog by Willacy *et al.* (2019), which utilizes full-waveform inversion to determine the event location, the horizontal location differences for events with $M_L \geq 0.5$ decrease slightly to a mean value of 563 m (Figure S5). We have refined the depth determination by including time picks from the borehole sensors for the time spanning mid-2015 to 2018, during which we observed a concentration of swarms as detailed below.

The increase in detection is consistent across the period studied. Many new detections are related to small events with signals close to the noise floor. However, a significant portion of new detections are the five bursts of small-magnitude (M_L 0.5 – 1.5) swarm-like sequences that double the earthquake rates between November 2016 and May 2017 (Figure 2a), which we discuss further in the "Swarm sequences" Section. Our catalog has the completeness magnitude (M_c) of 0.5 estimated using the maximum curvature method (Wiemer and Wyss, 2000). Here, we do not use the typical correction factor of 0.2 (Woessner and Wiemer, 2005), because it is advantageous to keep more events for the statistical analysis. The b-value slope of the frequency magnitude distribution is determined to be 0.86 by applying the B-Positive method (van der Elst, 2021) to all events with a conservative minimum magnitude difference of 0.2 (Figure 2b). Note that the B-Positive method does not require a complete catalog. With these additional events, the enhanced catalog can unlock new insights into the clustering behaviors of earthquakes in the Groningen gas field.

Clustering behaviors

The nearest-neighbor distance approach is applied to 726 earthquake epicenters in the enhanced catalog with $M_L \geq 0.5$. The distribution of nearest-neighbor distance η_j expanded in the form of rescaled time T_j and rescaled distance R_j is shown in Figure 3a. By fitting η_j with a 1-D Gaussian mixture model, we find the best-fit mode separator of $\log_{10} \eta_0 = -3.05$. We find that 522 events (72%) are independent, while the remaining 204 events (28%) appear to be clustered (Figure 3b).

The two-dimensional probability distribution of nearest-neighbor distances of the 100 shuffled catalogs are averaged and shown in Figure 3c. Since the rate of independent events vary only gradually during this period, their distribution similarly concentrates along a line with $\log_{10} T_j + \log_{10} R_j =$ constant with almost all reshuffled events (93%) having $\eta_j \geq \eta_0$, validating the approach and the chosen mode separator. The results are qualitatively similar if the earthquake hypocenters are used instead of the epicenters, accounting also for the depths (Figure S6). Furthermore, the independent events (those with $\eta_j \geq \eta_0$) have CoV of approximately one, consistent with them being Poissonian. If we were to choose $\eta_0 < -4$, events with $\eta_j \geq \eta_0$ include clusters as CoV becomes significantly greater than one (Figure S7).

The Schuster spectrum calculated for the non-declustered catalog shows low p-values, lower than expected for a Poisson process, which drifts to even lower value starting at a period of about 2-3 days (Figure S8a). This pattern shows that the catalog contains clusters (Ader and Avouac, 2013) and we can infer they have durations of a few days or eventually longer. However, if we use only the independent events, the drifting low p-values disappear (Figure S8b), further validating the choice of the value of the mode separator chosen.

We proceed to analyze the spatiotemporal evolution of the events from each of the two modes (Figure 4). The independent events align well with mapped faults and have the seismicity rate that is gradually changing with time. On the other hand, the clustered events show multiple lineations that do not align with mapped faults and occur as short-duration bursts of events in time. The most prominent clusters are the five bursts of small magnitude (M_L 0.5 – 1.5) swarm-like sequences occurring between November 2016 and May 2017. The others appear to be aftershocks of the larger $M_L > 2$ events. By construct, if a sequence has a foreshock, the mainshock will be identified as a clustered event rather than an independent event because the foreshock would be its parent, which explains why some of the larger events are identified as clustered.

The spanning tree created by connecting each event with its nearest neighbor if $\eta_j < \eta_0$ reveals 448 single-event clusters (62% of events) and 73 multievent clusters (38% of events). Their detailed statistics are shown in Figure 5. The average size of the multievent clusters is 3.8 events with a standard deviation of 3.6 events. The large standard deviation reflects significant variations in clustering behaviors. All earthquakes with $M_L > 2.5$ are a part of multievent clusters, with the number of events in the cluster growing with mainshock magnitude. On average, the largest aftershock is 1.5 magnitude unit lower than the mainshock, in line with those expected from Båth's law (Richter, 1958). The average leaf depth of these aftershock sequences is 1.3, indicating that most of the events are triggered by the mainshock rather than being aftershocks of aftershocks. On the other end of the spectrum, there are multievent clusters that exist as swarm-like sequences without a clearly identifiable mainshock ($M_{\text{mainshock}} - M_{\text{largest aftershock}} \ll 1$, contradicting Båth's law) and a larger value of average leaf depth (d_{leaf}) of up to 8.7. For an earthquake sequence with an average of two aftershocks for each earthquake, the cluster size (n_{clust}) would then be $2^{d_{\text{leaf}}}$. Therefore, this motivates using d_{leaf} of $\log_2 n_{\text{clust}}$ as a cutoff for binary classification between swarm-like and aftershock-like clusters. Considering only clusters with at least 5 events, we find 7 swarm-like clusters ($d_{\text{leaf}} \geq \log_2 n_{\text{clust}}$) with a total of 77 events (55% of clustered events) and 9 aftershock-like clusters ($d_{\text{leaf}} < \log_2 n_{\text{clust}}$) with a total of 64 events (45% of clustered events). The analysis suggests that the clustered events are slightly dominated by swarm-like sequences. Among the aftershock-like clusters, the events are 16% foreshocks, 14% mainshocks, and 70% aftershocks.

Swarm sequences

There were five noticeable swarm-like clusters between November 2016 and May 2017, each lasting 1 to 5 days and consisting of 10 to 20 events, with M_L ranging from 0.66 to 1.56 (Figure 6). Outside of this period, we did not find any other noticeable swarm clusters. Upon further investigation of their kinematics, all swarms migrate with velocities ranging from 3 to 50 km/day. We numbered the swarms from 1 to 5 based on the order that they occurred. The migration occurred along one single direction for swarms 1 and 2 and two different orthogonal directions for swarms 3 – 5. For swarms 3 and 4, there exists also ~ 15 hour pauses with no events before the migration direction switches. The migration directions do not follow mapped faults or other known features of the reservoir. While there are not enough events to determine the exact shape of the migration front, it is possible to model them with $\sqrt{4\pi D t}$ where D would be an apparent hydraulic diffusivity, and t is time. In the case of fluid-driven swarms, the fitted D would be related to the hydraulic diffusivity of the fault zones (Shapiro *et al.*, 1997), though with a conversion factor that accounts for the time delays associated with earthquake nucleation (Kim and Avouac, 2023). The swarms in our study have D ranging from 70 – 800 m^2/s, much larger than a commonly accepted range for fluid-driven swarms of 0.005 – 10 m^2/s (Amezawa *et al.*, 2021). In comparison to other swarms around the world, the scaling between migration velocity and duration places them closer to slow-slip events and swarms driven dominantly by slow-slip events than other injection-induced swarms (Danré *et al.*, 2022). We further discuss possible drivers for these swarms in "Possible drivers of swarm-like sequences" Section.

Another interesting observation is that the swarms occurred at a depth of between 1.5 to 2.5 km. While there could be some uncertainty with the absolute depth locations, they are certainly located toward the shallower side when compared to other earthquakes that are generally thought to be located near the top of the reservoir (Willacy *et al.*, 2019; Smith *et al.*, 2020). As a result, this would place them in the 1 – 2 km thick Zechstein evaporite (salt) above the anhydrite caprock, well above the gas reservoir (Figure 7).

Discussion

Comparison of clustered fraction with other studies

Induced earthquakes are known to have a lower proportion of clustered events than naturally occurring tectonic earthquakes due to high driving stresses from anthropogenic activities in comparison to tectonic loading (Schoenball *et al.*, 2015; Zaliapin and Ben-Zion, 2016; Cochran *et al.*, 2018; Martínez-Garzón *et al.*, 2018). Here, we compile in Table 1 the clustered proportion of seismicity from different regions as reported by previous studies. We find that the clustered events can account for up to 70% of naturally occurring tectonic earthquakes but no more than 30% of induced earthquakes. The estimate of 28% from this study places the Groningen gas field well within the range estimated for other induced seismicity settings. Other studies on the clustered proportion of seismicity from the Groningen gas field provide different estimates of the clustered proportion varying from a few percent up to 27%, which are generally lower than the 28% that we report here (Candela *et al.*, 2019; Muntendam-Bos, 2020; Post *et al.*, 2021; Trampert *et al.*, 2022). Among those that also uses the nearest-neighbor distance approach, Candela *et al.* (2019) finds 18% of clustered events between 1993 – 2016, while Muntendam-Bos (2020) finds only 6% of clustered events between 1995 – 2018, but the proportion increases to 22% if consider only the period between 2014 – 2018. On the other hand, Post *et al.* (2021) uses the statistics of the interevent times and finds a larger value of 27% for the clustered proportion. The scatter of the clustered proportion identified by the different studies can be attributed to various factors, including but not limited to: variation of earthquake rates and clustering behaviors with time (Trugman *et al.*, 2016; Martínez-Garzón *et al.*, 2018; Muntendam-Bos, 2020), accuracy of earthquake locations (Muntendam-Bos, 2020), and the five swarm sequences occurring between November 2016 and May 2017 that were not previously identified other seismicity catalogs, and the cutoff magnitude employed (Zaliapin and Ben-Zion, 2013a). By removing the five swarms, our estimate of the clustered proportion becomes 19%, which is almost equivalent to the estimate from Candela *et al.* (2019). We also calculate the clustered proportion using the different cutoff and find that the clustered proportion generally decreases with larger cutoff and becomes stable at between 18 – 20% as the cutoff exceeds M_L of 1.2 at which the five swarm sequences are excluded from the analysis (Figure 8).

Possible drivers of swarm-like sequences

Although the migration of swarms in the Groningen gas field can be modeled with a square root of time typically associated with fluid pressure diffusion (Shapiro *et al.*, 1997), it is unlikely that fluid plays any dominant role because of the following reasons. First, the migration direction should be along the maximum spatial pressure gradient, which follows the spatial derivative of the compaction rate. This contradicts the observations in which the migration direction seems to align more along the contours of constant compaction (Figure 9a). Second, the migration velocity is on the order of 10 km/day, which requires a much higher hydraulic diffusivity than the values typically expected for fluid-driven swarms (Amezawa *et al.*, 2021). Third, while fault slip can enhance permeability, allowing for faster diffusion rates, the migration directions do not follow mapped faults or any known structures. There may be other unmapped faults in which the migration follows as there are focal mechanisms with fault planes not orienting along the mapped faults (Willacy *et al.*, 2019). Nevertheless, because the swarms are located in the Zechstein salt well above the impermeable anhydrite caprock that allows the gas to be preserved for millions of years (Figure 7), the faults in the Zechstein layer are probably not hydraulically connected to the reservoir and are most probably located in the anhydrite fragments that are embedded within the Zechstein evaporite rather than in the evaporite itself which cannot support brittle fractures due to its viscous nature. Hence, the swarms cannot be driven by direct fluid contact.

Besides fluids, cascading earthquakes can create an apparent diffusive expansion front (Helmstetter and Sornette, 2002). However, the swarms consist of only small M_L 0.5 – 1.5 events which would correspond to a rupture dimension of ~ 15 – 40 m, much smaller than the average distance of ~ 1 km between events (Figure 6). While there could exist a chain of smaller undetectable events that connect the larger ones, this is unlikely as our deep-learning-based workflow should be able to detect some events below M_L 0.5 (Figure 2), but we detect none. Therefore, cascade triggering is also unlikely.

These swarms occurred just after the period of accelerated compaction (Figure 9b), suggesting they might be related to the large strain rate from such period that could trigger swarms in the

Zechstein layer above the reservoir. However, since the compaction rate seems to be more correlated with the rate of independent events rather than the rates of all events (Figure S9), some additional mechanisms are required to connect compaction to the swarms. While seismic events in the salt are rare because salt is highly ductile they can occur in case of large strain rates, for example related to the collapse of mining cavity (Kinscher *et al.*, 2016) or fault creep (Barnea Cohen *et al.*, 2022), or in relation to fluid injection (Lei *et al.*, 2019). Alternatively, these events could also occurred within the anhydrite fragments embedded in the salt (Spetzler and Dost, 2017). Since there are no mining activities in the Zechstein layer and that the faults in this layer are most probably not hydraulically connected to the reservoir, propagating episodes of aseismic deformation is the most probable mechanism. While there are no detectable geodetic signals in either GPS on InSAR during the time of the swarms, aseismic creep may locate too deep or being too small to be detected. Swarms that are driven by aseismic slip generally propagate at high velocity in the order of km/hr (Lohman and McGuire, 2007; Sirorattanakul *et al.*, 2022), which is consistent with the observations of the Groningen swarms. The aseismic fault creep could occur within the fragments of anhydrite embedded in the Zechstein evaporite. Such creep can be driven by the long-range poroelastic stress changes incurred by pore pressure change in the reservoir. Poroelastic effects are indeed needed to explain both the surface subsidence and the induced seismicity at Groningen and are therefore explicitly included in most models (Bourne *et al.*, 2014; Buijze *et al.*, 2017; Dempsey and Suckale, 2017; Candela *et al.*, 2019; Smith *et al.*, 2022) . Alternatively, aseismic fault creep may be driven by stress induced by bulk creep in the surrounding Zechstein evaporite as the salt redistribute, possibly in response to the disturbances from the historic gas production. When faults are moderately stressed, fluid-induced aseismic creep can outpace the pressure diffusion front and trigger a seismicity front that propagates at velocities that are orders of magnitude larger than the fluid diffusion (Bhattacharya and Viesca, 2019; Wynants-Morel *et al.*, 2020; Sáez *et al.*, 2022). Since these swarms are not driven directly by stress changes from the industrial operations, they are not yet accounted for in induced seismicity forecasting models for the Groningen gas field.

Conclusions

By applying a deep-learning-based workflow for earthquake detection to seismic data from the Groningen gas field, we identify and locate a total of 1369 events from 2015 – 2022, almost two times more than the standard KNMI catalog. Despite being automatically generated products, the locations and magnitudes of the overlapping events display a high degree of similarity with the KNMI catalog. Analysis of the nearest-neighbor distances reveals that the clusters account for 28% of all events. Among the clustered events, approximately half are swarm-like clusters , while the remaining half are aftershock-like clusters. The swarm-like clusters include five distinct swarm sequences that migrate at incredibly fast velocities between 3 – 50 km/day along directions that do not follow mapped faults or existing structures and frequently exhibit a sharp turn in the middle of the sequence. Based on the observations of fast velocities and their depths in the Zechstein salt above the reservoir caprock, the swarms are most likely not driven by fluids but rather other aseismic processes such as propagating aseismic creep. The magnitude of these swarms is within the detectable range of the KNMI catalog, but they were not previously identified. With a better catalog, we can enhance our understanding of the mechanics of earthquake clusters and allow us to better incorporate their contributions to seismic hazards into induced seismicity forecasting models.

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Data and Resources

Raw seismic waveforms were accessed through the ORFEUS (Observatories and Research Facilities for European Seismology) FDSN (International Federation of Digital Seismograph Networks) client via a python script using the package Obspy (https://docs.obspy.org/; Beyreuther *et al.*, 2010). 3D seismic velocity and faults map were provided to us by Shell Global Solutions International B.V. Computer programs used to generate the enhanced seismicity catalog are previously published and can be found in the following references: seismic phase detection software PhaseNet (https://github.com/AI4EPS/PhaseNet; Zhu and Beroza, 2019), seismic phase association software GaMMA (https://github.com/AI4EPS/GaMMA; Zhu *et al.*, 2022), hypocenter inversion software HypoSVI (https://github.com/Ulvetanna/HypoSVI; Smith *et al.*, 2021). The seismicity catalog from the Royal Netherland Meteorological Survey (KNMI) is available online at www.knmi.nl. Matlab version 2020a were used to analyze data and prepare figures. The enhanced seismicity catalog generated in this study along with the picks of arrival times and codes used to analyze them are made available online at CaltechDATA repository (links will be provided after revisions).

Declaration of Competing Interests

The authors acknowledge that there are no conflicts of interest available.

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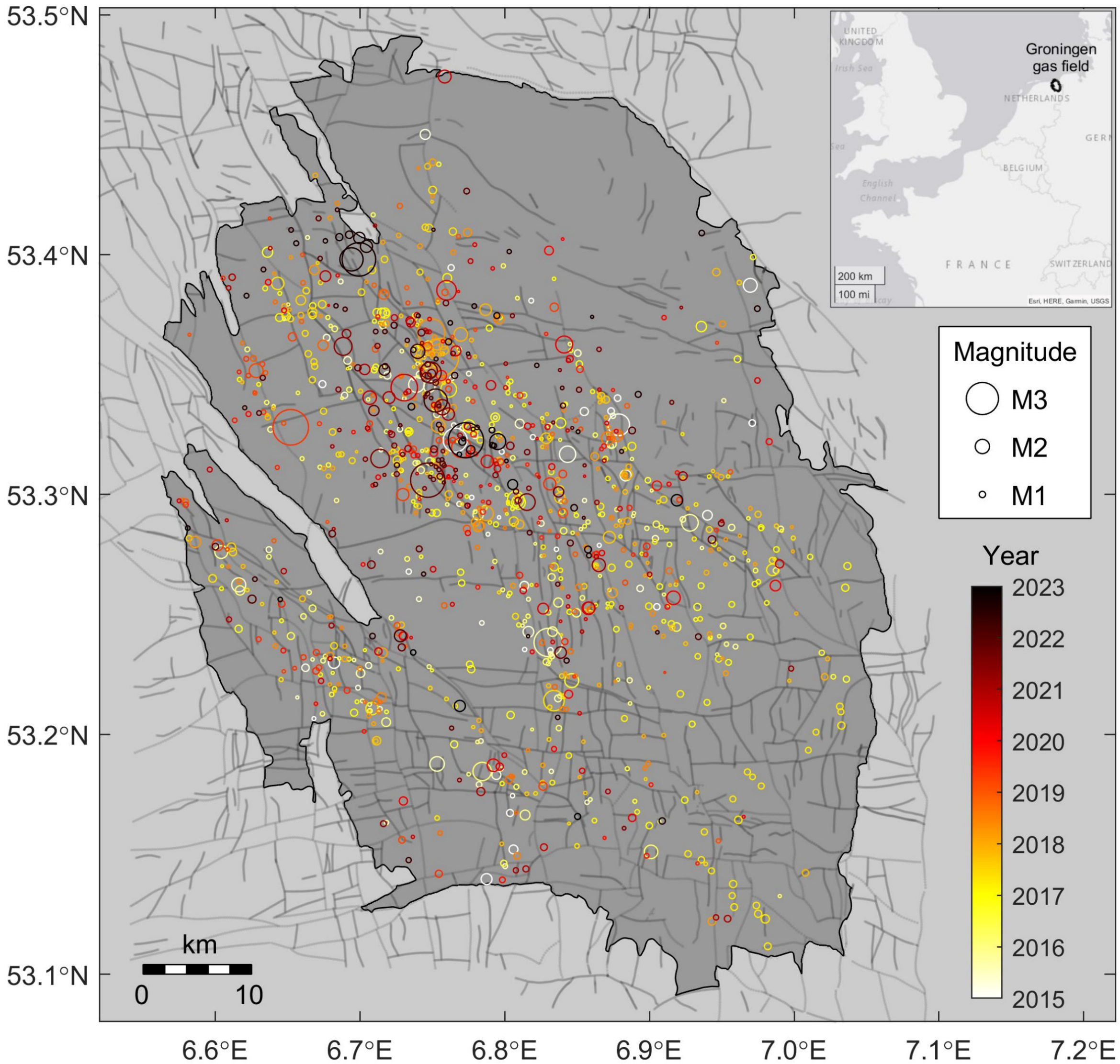


Figure 1. Map of induced seismicity in the Groningen gas field from 2015 – 2023 that were detected and located in this study using a deep-learning-based workflow. Circles show events with size representing the local magnitude and color representing the occurrence time. Black line shows the outline of the reservoir. Gray lines show mapped faults. The inset shows the location of the gas field within Europe.

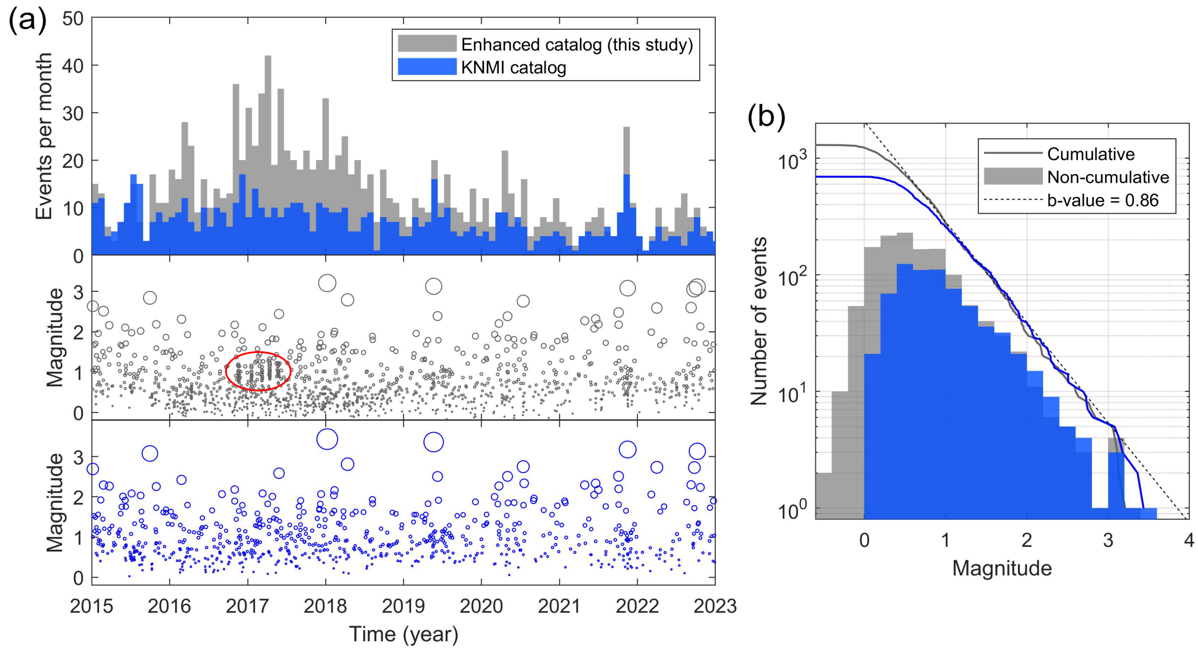


Figure 2. Enhanced seismicity catalog. (a) Comparison between our enhanced seismicity catalog and the standard catalog from the Royal Netherlands Meteorological Institute (KNMI). The top panel compares number of detected events per month. The middle panel shows distribution of event magnitude vs. time for the enhanced catalog. The red circle highlights the five newly detected swarm sequences. The bottom panel is the same as the middle but for the KNMI catalog. (b) Frequency-magnitude distribution from the two catalogs. The dashed line represents the Gutenberg-Richter exponential distribution with the b-value slope of 0.86 estimated from the enhanced catalog using B-Positive method (van der Elst, 2021). The completeness magnitude (M_c) of the enhanced catalog is estimated to be approximately 0.5.

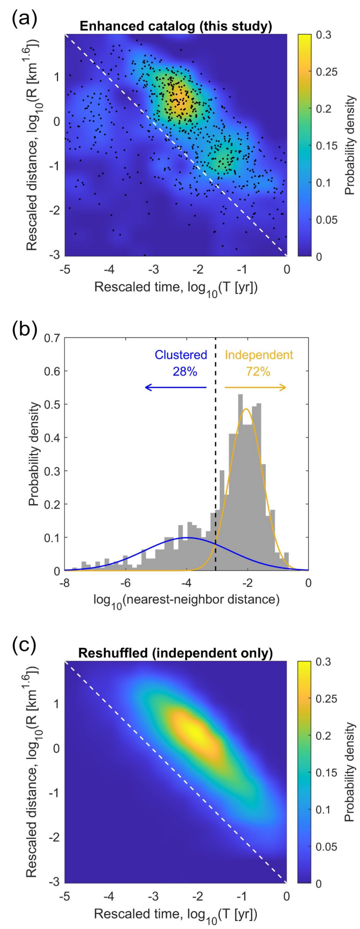
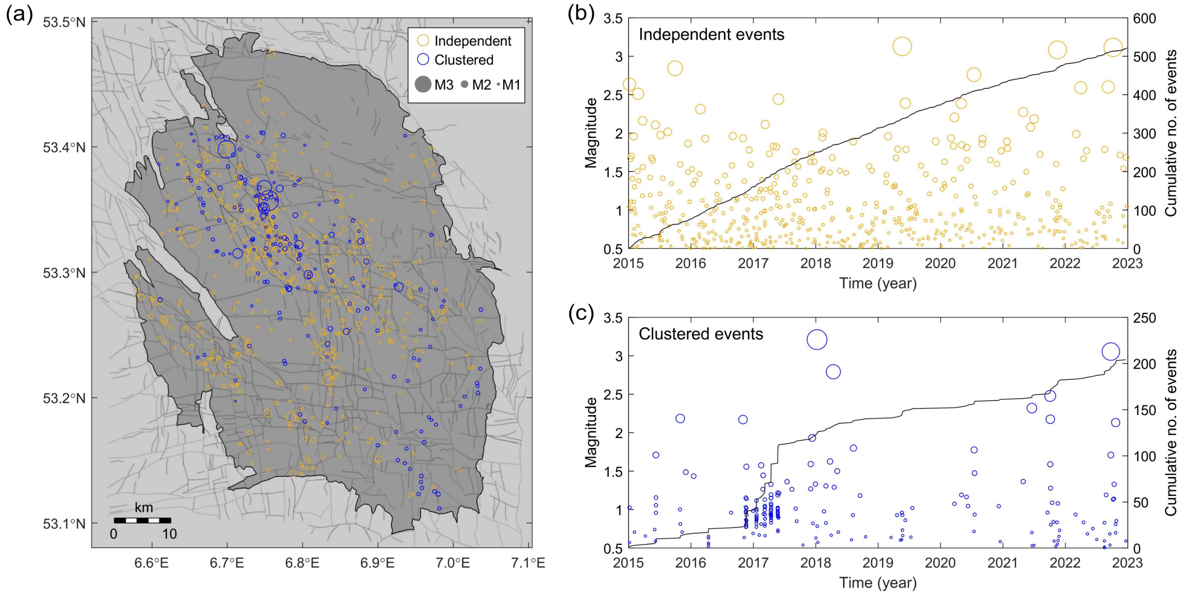


Figure 3. Nearest-neighbor clustering analysis performed on our enhanced seismicity catalog with $M_L \geq 0.5$. Only epicenters are used and the fractal dimension ($\boldsymbol{d_f}$) is taken to be 1.6. (a) A joint 2-D distribution of the rescaled time and rescaled distance. Each of the black dots represent proximity of each event to a parent event. (b) Histogram of the nearest-neighbor proximity distance with curves showing the two Gaussian distributions representing the two modes derived from 1-D Gaussian mixture model. (c) The average joint distribution of the rescaled time and rescaled distance derived from 100 catalogs created from reshuffling locations and magnitudes of independent events. The diagonal white dashed lines in panels (a) and (c) and black vertical dashed line in panel (b) mark the mode separator ($\eta_0 = 10^{-3.05}$) used to perform binary classification of events into either independent or clustered.



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800 **Figure 4.** Distribution of independent vs. clustered events for $M_L \geq 0.5$ from our enhanced seismicity catalog. (a) Spatial distribution of events color coded by the mode they belong to. (b) Magnitude and cumulative number of events vs. time distribution of the independent events. (c) Same as (b) but for clustered events.

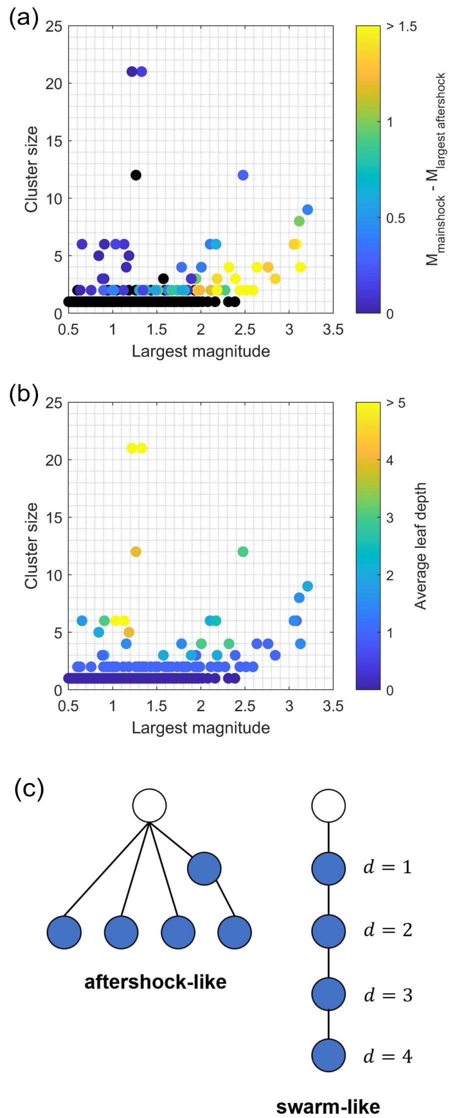

Figure 5. Statistics of the identified clusters. (a) Cluster size (number of events) vs. magnitude of the largest event color coded by the magnitude difference between mainshock and largest aftershock. Black circles denote the case with only one event in the cluster or when the largest earthquake is the last one in the sequence. (b) is the same as (a) but color coded by the average leaf depth. (c) A schematic showing aftershock-like and swarm-like sequences. Aftershock-like sequence has smaller average leaf depth than swarm-like sequence, but each event produces more offsprings.

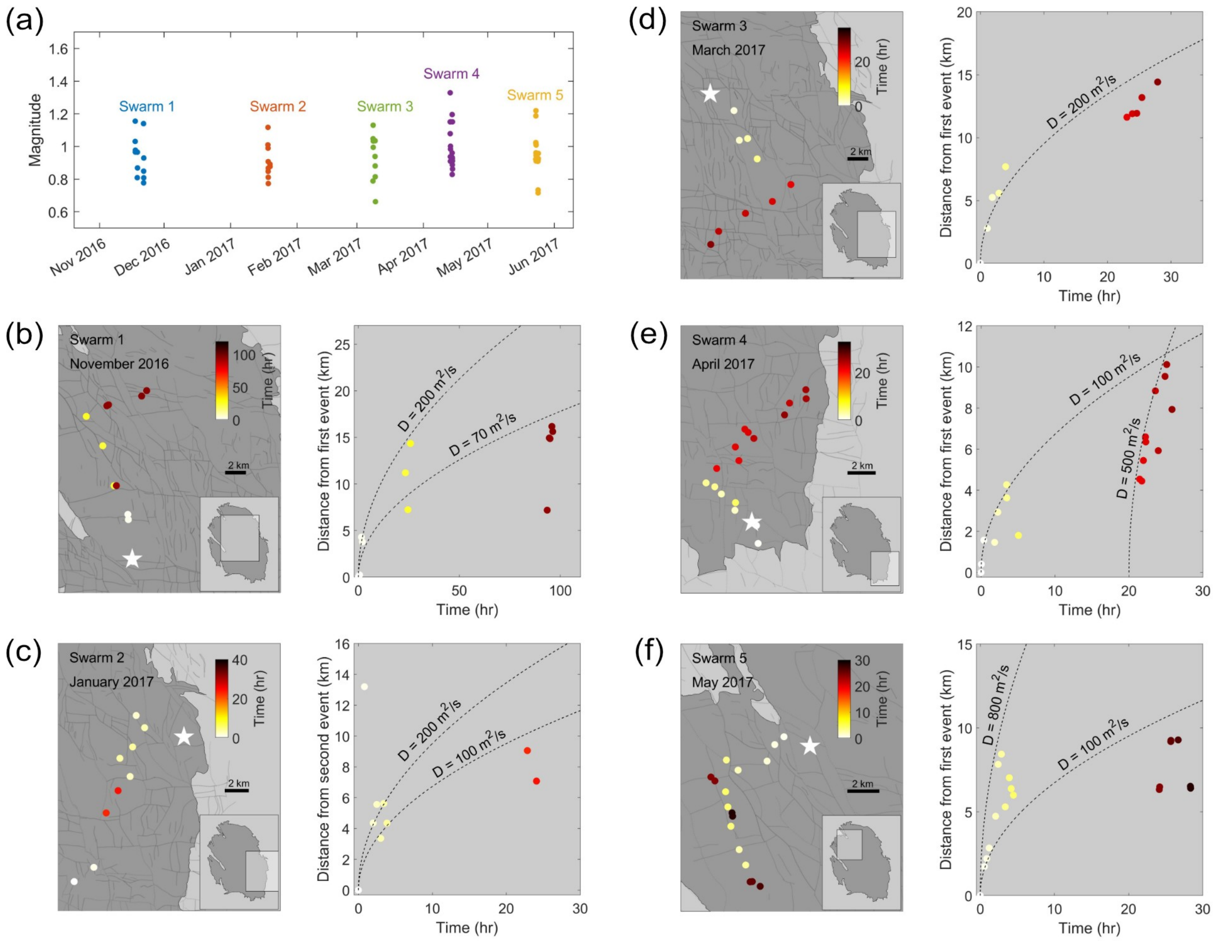

Figure 6. Fast propagating earthquake swarms. (a) Magnitude vs. time of the five distinct bursts of swarm-like sequences. (b) – (f) show the spatiotemporal evolution of these five swarms. The white stars mark the second event in swarm 2 and first event in all other swarms. The dashed lines show the predicted expansion for the different values of apparent hydraulic diffusivity D.

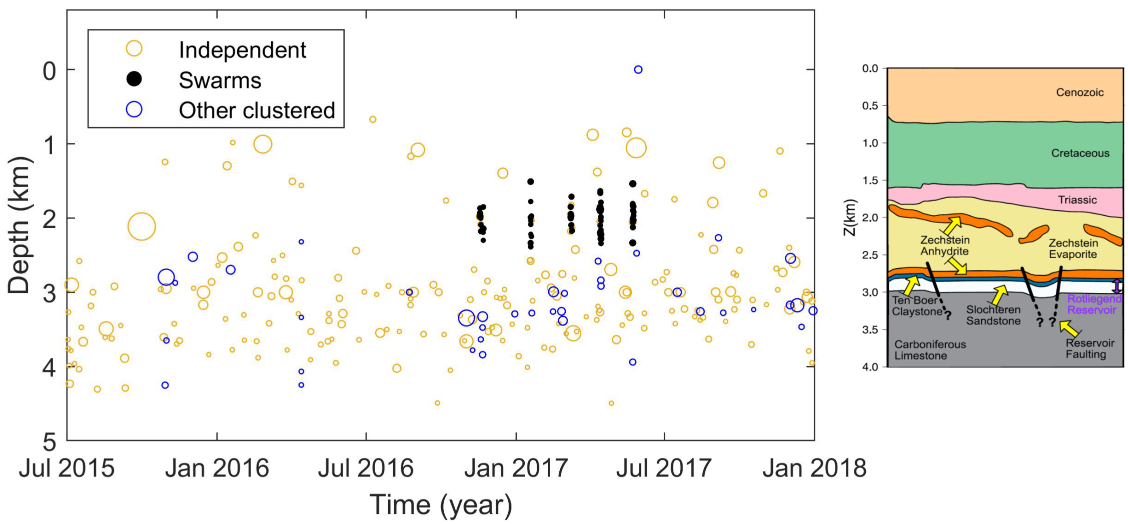

Figure 7. Depth distribution of earthquakes with $M_L \geq 0.5$ from our enhanced seismicity catalog with colors identifying whether they are independent, fast propagating swarms shown in Figure 6, or other clustered events, along with a schematic showing a depth cross-section of lithologies taken from Smith et al. (2019). Only the time period where we have picks from both surface and borehole sensors are shown. The five swarm sequences are located in the Zechstein evaporite.

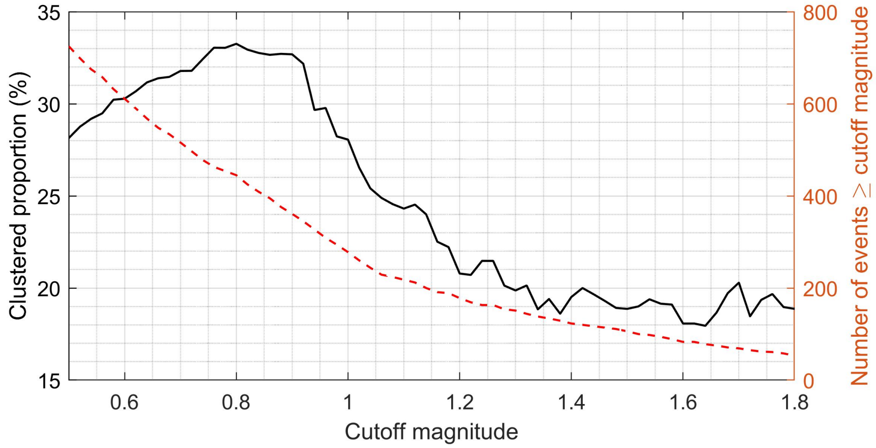

Figure 8. Variations of clustered proportion for the different cutoff magnitude. The dashed line shows the number of events larger than or equal to a given cutoff magnitude.

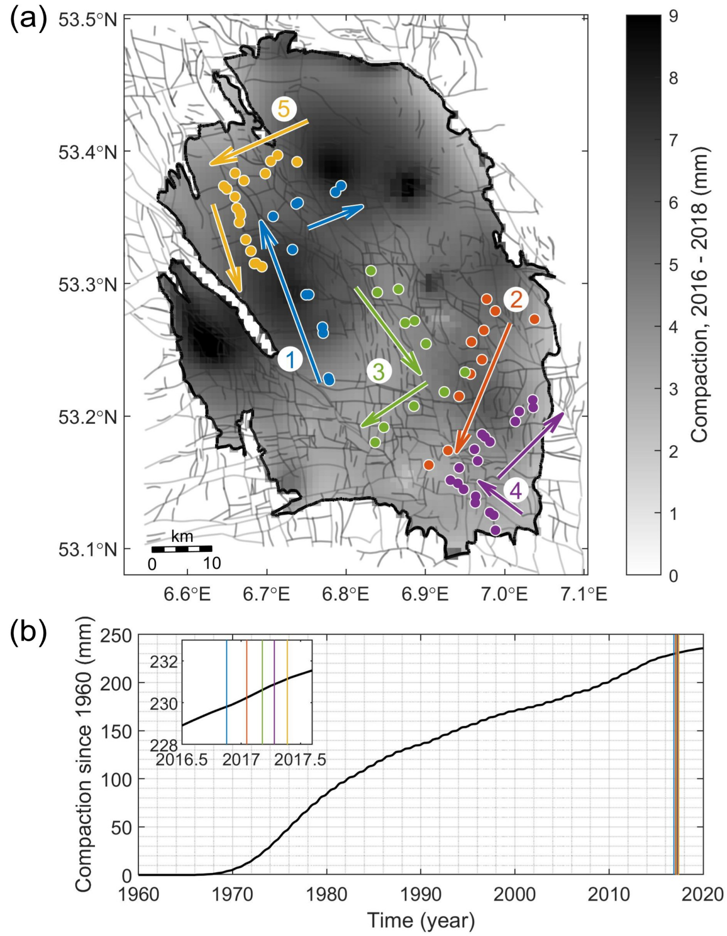

Figure 9. Comparison of swarms with reservoir compaction. (a) Spatial distribution of modelled reservoir compaction between 2016 and 2018. The calculation is done using a simple expression $C = C_m \cdot \Delta P \cdot h$ relating compaction C with the compressibility C_m from Smith *et al.* (2019) constrained with geodetic data, pressure depletion ΔP from Acosta *et al.* (2023) calculated using a simplified reservoir model from Meyer *et al.* (2023) constrained with pressure measurements from the borehole sensors, and the reservoir thickness h. The circles with different colors denote the five different swarms shown in Figure 6. (b) Average compaction in the reservoir vs. time. The vertical lines denote the timing of the five swarms. The inset shows a zoomed-in during the time of swarms.

Table 1. A compilation of clustered fraction of seismicity from different regions. With the exception of Post *et al.* (2021), which utilizes the statistics of interevent times, all other studies utilized the nearest-neighbor distance approach (Zaliapin *et al.*, 2008; Zaliapin and Ben-Zion, 2013a).

Region	Type of seismicity	Magnitude cutoff	Clustered fraction
Southern California (Zaliapin and Ben-Zion, 2013a)	Mostly tectonic	2	0.70
San Jacinto fault zone, California, USA (Zaliapin and Ben-Zion, 2016)	Tectonic	1	0.34
Coso geothermal field, California, USA (Zaliapin and Ben-Zion, 2016)	Mixed	1	0.44
Salton Sea geothermal field, California, USA (Zaliapin and Ben-Zion, 2016)	Mixed	1.5	0.69
Geysers geothermal field, California, USA (Zaliapin and Ben-Zion, 2016)	Induced	1.0	0.17
TauTona gold mine, South Africa (Zaliapin and Ben-Zion, 2016)	Induced	1.5	0.12
Saltwater disposal, Oklahoma (Cochran *et al.*, 2020)	Induced	0.95	0.30
Hydraulic fracturing in western Alberta, Canada (Karimi and Davidsen, 2023)	Induced	0.2	0.25

Groningen gas field, Netherlands, KNMI catalog (Candela *et al.*, 2019)	Induced	1.0	0.18
Groningen gas field, Netherlands, KNMI catalog (Post *et al.*, 2021)	Induced	1.3	0.27
Groningen gas field, Netherlands, KNMI catalog between 01/1995 – 01/2019 (Muntendam-Bos, 2020)	Induced	1.2	0.06
Groningen gas field, Netherlands, KNMI catalog between 05/2014 – 01/2019 (Muntendam-Bos, 2020)	Induced	1.2	0.22
Groningen gas field, Netherlands, enhanced catalog (this study)	Induced	0.5	0.28
Groningen gas field, Netherlands, enhanced catalog (this study)	Induced	1.2	0.21