Forecasting mining microseismicity using the stochastic ETAS model

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Summary

Mining activities bring about alterations in the subsurface stress field, potentially resulting in seismic events. It is imperative to devise strategies for forecasting and avoiding significant events to ensure the safety and efficiency of mining operations. For example, microseismicity is observed in soft rock potash mines, predominantly instigated by rock excavations but also influenced by delayed effects of plastic creep in soft rocks. Understanding the statistical aspects of microseismicity in potash mines, or similar mining environments, is crucial for earthquake hazard assessment and risk mitigation. This study focuses on the temporal evolution of microseismicity in a potash mine in Saskatchewan, employing the Epidemic Type Aftershock Sequence (ETAS) stochastic model to estimate the occurrence rate. The derived parameters reveal swarm-type characteristics with limited inter-event triggering. Additionally, a Bayesian predictive framework is applied to calculate the probabilities of the largest expected events above a certain magnitude within specified forecasting time intervals during the sequence evolution. This probabilistic approach incorporates uncertainties in model parameters using Markov Chain Monte Carlo sampling of the posterior distribution to assess parameter variability. Several statistical tests are conducted to evaluate the credibility of retrospective forecasts against observed microseismicity. Results demonstrate the efficacy of the developed approach in accurately forecasting the number and intensity of events while providing a framework for computing probabilities associated with the largest expected events. The methodology offers a comprehensive means of considering uncertainties in model parameters, enhancing the reliability of seismic event forecasts in mining operations.

Methods

In this work, we investigate and model the evolution of microseismicity in a potash mine in Saskatchewan. Our main goal is to discern the statistical features of microseismicity and determine the probabilities for the occurrence of the largest expected events surpassing a specified magnitude within designated forecasting time frames. To achieve this objective, we apply the ETAS model (Ogata, 1988), known for its effective approximation of seismicity rates.

To conduct a retrospective statistical analysis of mining microseismicity, it is crucial to separate the time interval into multiple segments. This segmentation is essential for integrating the influence of prior events on the occurrence rate of subsequent events, ultimately minimizing uncertainty in parameter estimation.

The occurrence of microseismicity can be envisioned as a cascade of triggered events with scale-invariant features. To understand and quantify this phenomenon, we employed the ETAS model to characterize the occurrence rate of sequence.

The temporal ETAS model (Ogata, 1988) consists of two key components. The first component, denoted by the variable, μ, represents a constant rate reflecting the assumption that events occur randomly at a specific rate, following a Poisson process. This component represents the background rate of events. The second component introduces the idea that each event in the past can potentially trigger subsequent events. Consequently, the overall observed rate is a combination of the background rate and the contributions from all preceding events, including both triggered and background events. This dual-component structure allows for a more comprehensive understanding of the complex interplay between random occurrences and the influence of past events on the current rate of microseismicity.

For computing the probabilities associated with the largest expected events, we employ a Bayesian predictive framework that considers uncertainties linked to the model parameters (Shcherbakov et al., 2018, 2019). This framework integrates Markov Chain Monte Carlo sampling of the posterior distribution, generating parameter chains to gauge their variability.

Additionally, we perform statistical tests to evaluate the reliability of retrospective forecasts by comparing them against observed microseismicity data (Shcherbakov et al., 2018, 2019; Shcherbakov, 2021; Sedghizadeh & Shcherbakov, 2022). This comprehensive analysis aims to enhance our understanding of the factors and mechanisms influencing mining seismicity occurrences, thereby contributing to the development of strategies for forecasting and mitigating rare events.

Mining seismicity data

The studied mining microseismicity sequence includes a timeframe spanning from May 1st, 2019, to July 9th, 2021, containing a total of 11,633 recorded events with a magnitude range from -2.97 to 0.56. The events associated with network calibration surface shots, between February 12th, 2021, and February 19th, 2021, were manually excluded. This exclusion resulted in a reduction of the overall number of recorded events to 9,267. The spatial distribution of these microseismic events is visually represented in Figure 1.

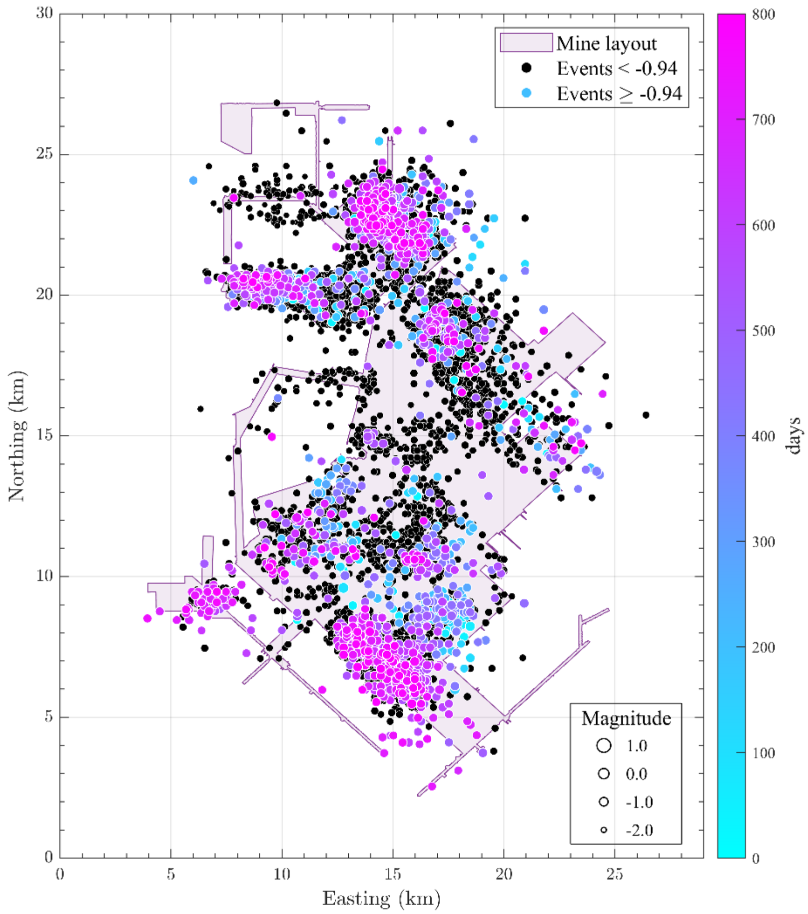

Figure 1. The spatial distribution of microseismic events within a potash mine located in Saskatchewan, Canada. The dataset spans from May 1, 2019, to July 9, 2021. In the plot, black and coloured circle symbols denote events with magnitudes below $m < -0.94$ and above $m \geq -0.94$, respectively. The colours of the circles correspond to the time of occurrence, as indicated by the colour bar, with the timeline commencing on May 1, 2019. The light purple area on the plot outlines the layout of the mine, encompassing the mine shafts and tunnels.

Results

The frequency-magnitude statistics were modelled using the exponential distribution with a magnitude binning of 0.01. The magnitude of completeness, denoted as m_c = -0.94 derived from the G-R *b*-value stability method (Sedghizadeh et al., 2023).

The ETAS model was employed to estimate the microseismicity rate originating from a potash mine in Saskatchewan, Canada. Model parameters were determined using the maximum likelihood method for various target time intervals, [T_s, T_e]. Initially, the fitting process covered the entire catalogue duration, with the training time interval defined as [T_0, T_e] = [0, 800.57] days. During this process, the ETAS model parameters were estimated for a cutoff magnitude m_c = -0.94, and within the specified target time interval [T_s, T_e] = [102, 800.57]. An adequate fit to the observed data was achieved by the model (Figure 2). Also, several intervals were initiated from T_s = 102.0 and extended up to T_e = [400, 430, …, 760] days was utilized to fit the ETAS model.

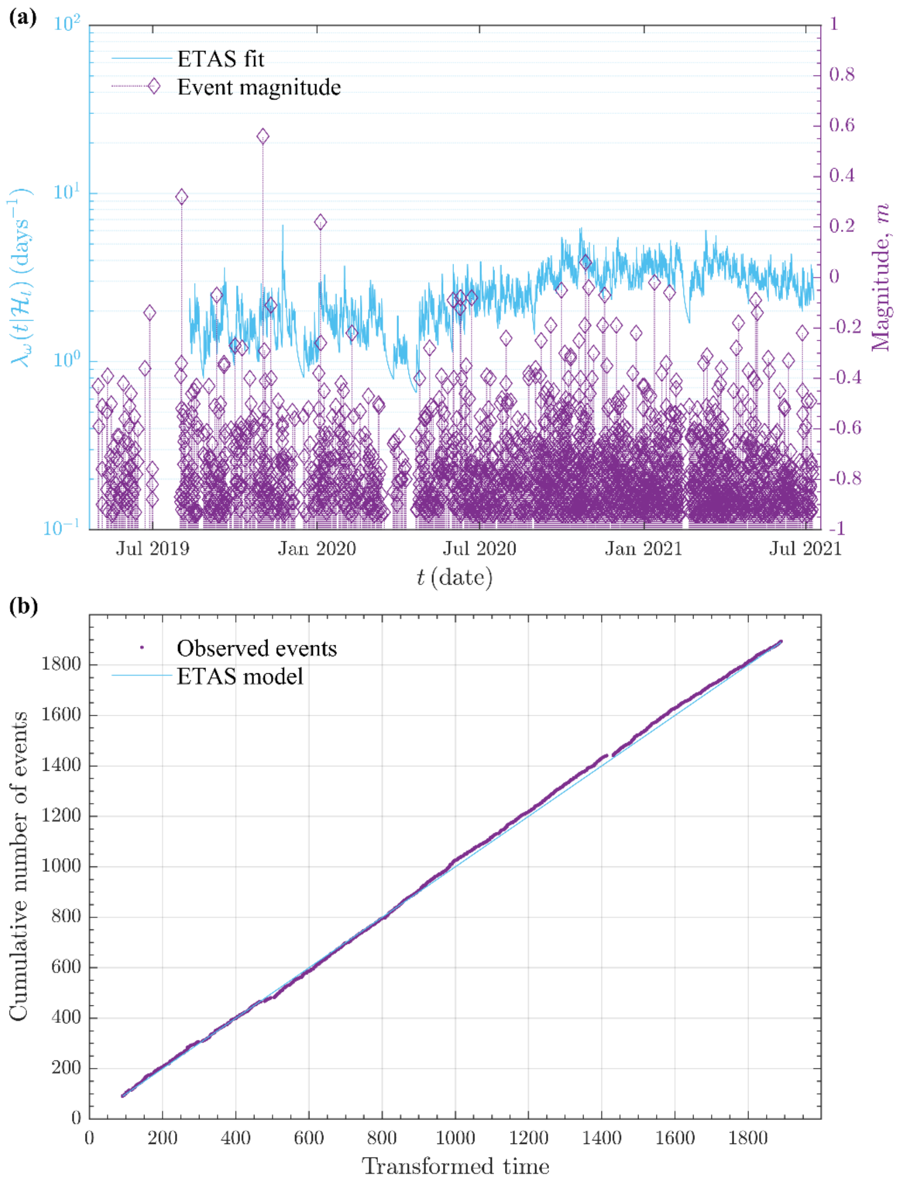

Figure 2. The fit of the ETAS model to mining microseismicity within the targeted time interval [T_s, T_e] = [102, 800.57] days. a) The microseismicity sequence and corresponding event magnitudes throughout the analyzed period for all events above $m \geq -0.94$. b) The cumulative number of observed events in transformed time, along with the corresponding rate of the ETAS model during the analyzed time interval for all events above $m \geq -0.94$. The derived parameters, accompanied by 95% confidence intervals, are as follows: $\mu = 0.22 \pm 0.62$, $A = 0.45 \pm 0.52$, $c = 0.47 \pm 0.89$, $p = 1.19 \pm 0.18$, and $\alpha = 0.82 \pm 0.69$.

Moreover, the analysis includes the examination of the evolution of probabilities for the occurrence of the largest expected events with a magnitude greater than or equal to *m* within a forecasting time interval of ΔT = 30 days after each target time interval, T_e = [400, 430, …, 760] days. Figure 3 illustrates the progression of calculated probabilities for events exceeding m_{ex} > 0.0, 0.25, 0.5. A notable increase in probabilities is observed around 520 days into the sequence, preceding the occurrence of a cluster of larger events.

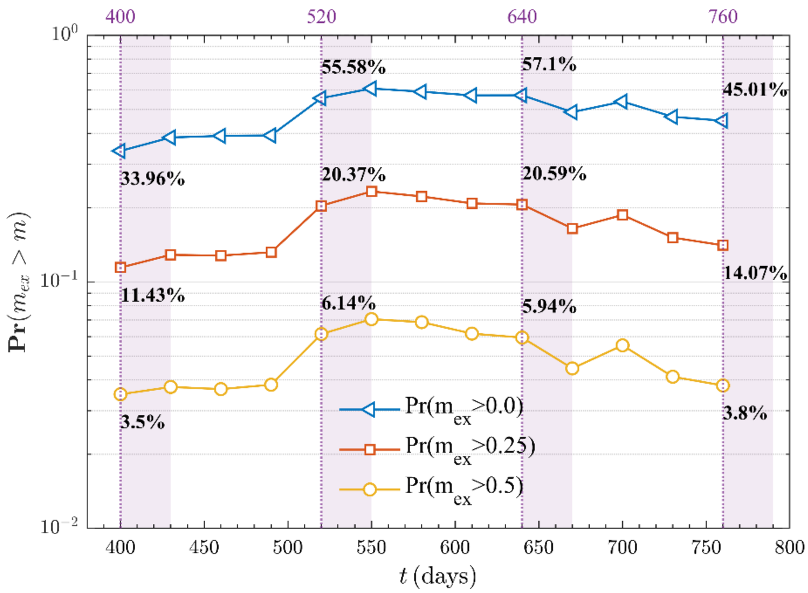

Figure 3. The progression of probabilities for the occurrence of the largest expected events with magnitudes greater than or equal to 0.0, 0.25, and 0.5. The probabilities are evaluated within a forecasting time interval of ΔT = 30 days after each training time interval, T_e = [400, 430, …, 760] days.

The effectiveness of the BPD forecasting method was assessed for forecasting both the number and magnitudes of seismic events. We employ the statistical test to assess the agreement between the number of forecasted events and the actual observed events. Also, we examine the consistency of magnitude distribution in the forecasted seismic events.

Conclusions

In summary, this study establishes the ETAS model as a reliable tool for forecasting microseismic events in the mine environment, showcasing its effectiveness in forecasting both the number and magnitude distribution of events. This method not only unveils the factors and mechanisms influencing mining seismicity but also contributes to the development of strategies for forecasting and mitigating significant events. The proposed framework adeptly forecasts event numbers and intensity within the analyzed sequence, enabling the detection of deviations from typical mining-induced seismicity rates. Consequently, this study presents a robust methodology applicable to earthquake hazard assessment and risk mitigation in mining operations.

Future research endeavours should prioritize refining our modelling approach by incorporating additional geological and geomechanical factors while systematically addressing the limitations identified in this study.

Acknowledgements

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References

Ogata, Y. (1988). Statistical models for earthquake occurrences and residual analysis for point processes, J. Am. Stat. Assoc., 83(401), 9–27

Sedghizadeh, M. & Shcherbakov, R. (2022). The analysis of the aftershock sequences of the recent mainshocks in Alaska, Appl. Sci, 12(4).

Sedghizadeh, M., van den Berghe, M., & Shcherbakov, R. (2023). Statistical and clustering analysis of microseismicity from a Saskatchewan potash mine, Front. Appl. Math. Stat., 9, 1126952

Shcherbakov, R. (2021). Statistics and forecasting of aftershocks during the 2019 Ridgecrest, California, earthquake sequence, J. Geophys. Res., 126(2), e2020JB020887.

Shcherbakov, R., Zhuang, J., & Ogata, Y. (2018). Constraining the magnitude of the largest event in a foreshock-mainshock-aftershock sequence, Geophys. J. Int., 212(1), 1–13.

Shcherbakov, R., Zhuang, J., Zoller, G., & Ogata, Y. (2019). Forecasting the magnitude of the largest expected earthquake, Nat. Commun., 10, Art. 4051.