Proceedings World Geothermal Congress 2026, Calgary, Canada, June 8—11, 2026

Spatiotemporal estimation of injected water migration in reservoirs from microseismicity using statistical analysis: A case study in the Okuaizu geothermal field, Japan

Naoki Aoyagi[1]*, Kyosuke Okamoto[1], Yusuke Mukuhira[2] , Hiroshi Asanuma[1]
National Institute of Advanced Industrial Science and Technology[1]*, Tohoku University[2]
e-mail : naoki-aoyagi@aist.go.jp

INTRODUCTION

Temporal changes in parameter μ of the Epidemic-Type Aftershock Sequence (ETAS) model interpreted as the occurrence rate of microseismicity induced by fluid flow (e.g., case of geothermal field, Hainzl and Ogata 2005). The ETAS analysis can be performed well when a sufficient number of earthquake time series data (origine time, hypocenter locations, and magnitude) are available. To estimate the temporal changes of μ, it is necessary to divide portions of the earthquake time-series data by moving analysis windows. However, depending on the length of the analysis window (i.e., the number of earthquake events), a trade-off arises between the accuracy of the estimated μ and the resolution of temporal changes of μ. In geothermal field, where fluid activity is intense, microseismic events may have ETAS parameters different from those of ordinary tectonic earthquakes, suggesting the need for investigations specifically focused on seismicity in geothermal field. In this study, for the aim of advancing microseismic monitoring in geothermal fields and monitoring fluid flow, we investigated how characteristics of microseismic time series in geothermal fields (such as the number of events and magnitude ranges) affect the variation of ETAS model estimation.

METHODS

[Purpose]

To accurately evaluate the temporal variation of the μ value in the ETAS model for geothermal filed, it is necessary to examine the conditions for the number of events and time window length in the catalog used for the ETAS analysis.

[Estimation the ETAS model]

1.The ETAS model (Ogata 1988) :

$$\lambda_\theta(t|\mu,K,c,\alpha,p) = \mu + \sum_{t_i<t} \frac{Ke^{\alpha(M_i-M_c)}}{(t-t_i+c)^p} \quad (1)$$

μ : microseismicity rate according to a Poisson process.

2. Maximum likelihood estimates:

$$\log L(\mu,K,c,\alpha,p) = \sum_{i=1}^{N} \log \lambda_\theta(t_i) - \int_S^T \lambda_\theta(t)dt \quad (2)$$

The parameters μ, K, c, α and p were estimated by maximizing the log-likelihood function log$L$.

3. Target: 8,286 microseismic events that occurred in the Okuaizu geothermal field between November 1, 2017, and March 25, 2024, with a magnitude of completeness, Mc = -1.05

[Evaluation of the effect of the number of events]

1.Using the ETAS parameters obtained for the Okuaizu geothermal field, a synthetic catalog containing >8,000 events was generated.

2. ETAS analyses were conducted using analysis windows with a fixed number of target events.

3. Steps (1) and (2) were repeated 1,000 trials with different random seeds for catalog generation.

4. The mean and standard deviation of estimated parameters for each event-number condition were compared with the original ETAS model parameters (true values).

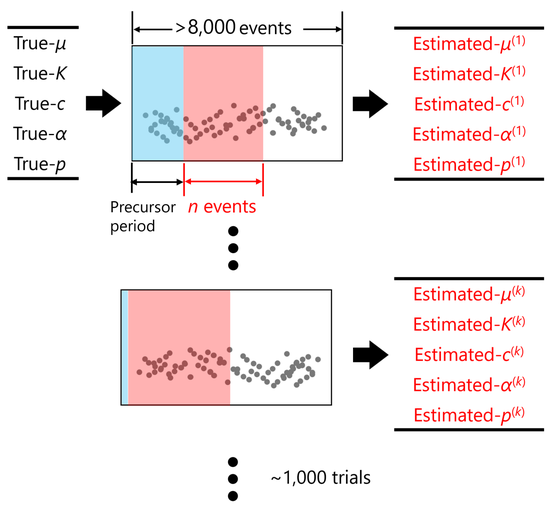
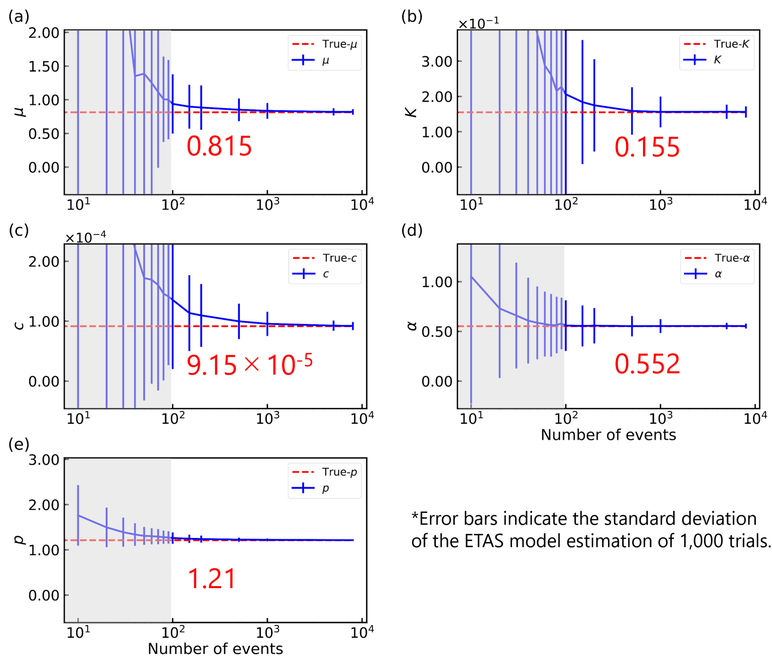


Figure 1. Schematic diagram of sub-catalogs and ETAS parameter estimation trials using time windows.

DEPENDENCE OF ETAS MODEL ESTIMATION ON EACH TIME WINDOW CONDITION

Mean and SD of each parameter estimate for each event condition



*Error bars indicate the standard deviation of the ETAS model estimation of 1,000 trials.

Figure 2. Mean and 1000 trial SD of each parameter estimates for each event condition. (a): μ, (b): K, (c): c, (d): α, (e): p. Red dashed lines: true ETAS parameters.

Distribution of parameter estimates for each event density

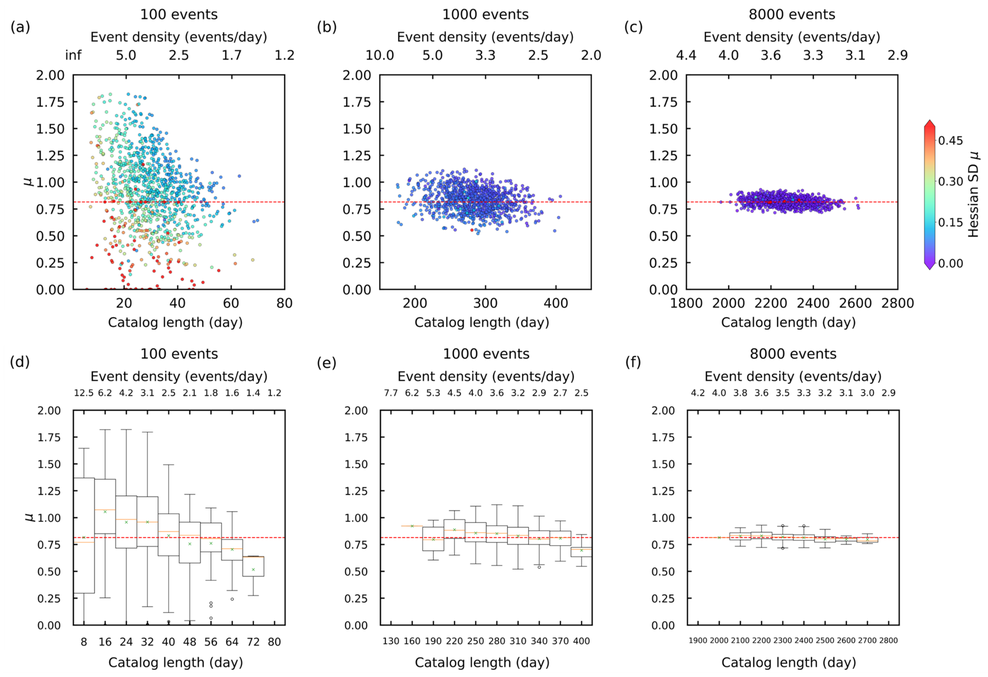


Figure 3. (a-c): Distribution of parameter estimates and their Hessian SDs for each time window length and event density. (d-f): Box plots of parameter estimates for each time window length and event density. (a, d): 100 events, (b, e): 1,000 events, (c, f): 8,000 events. Red dashed lines: true μ.

Applying to real-data: Okuaizu geothermal field (Temporal changes in μ)

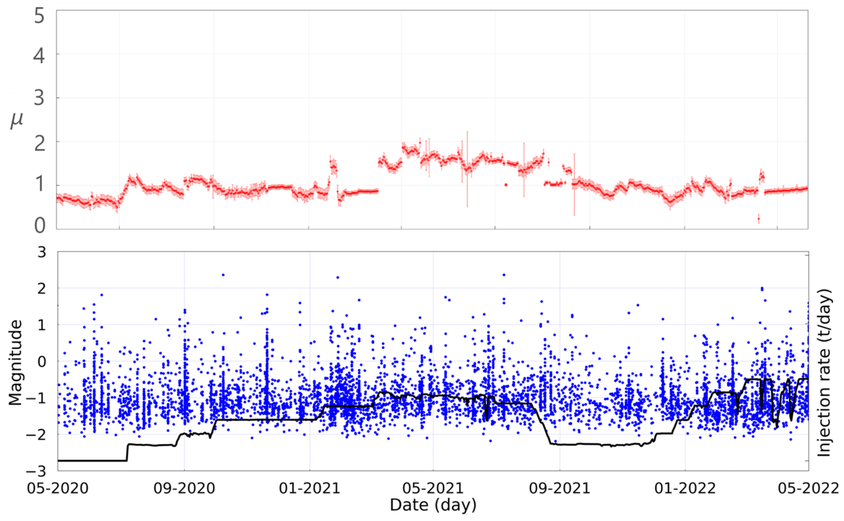


Figure 4. Temporal changes in μ and injection rate from May 1, 2020 to May 1, 2022 in Okuaizu geothermal field. (Top): Temporal μ, (bottom): Magnitude of events and water injection rate.

RESULTS AND DISCUSSION

- The mean values of μ, K, c and p asymptotically approached the true values exponentially as the number of events increased, with p converging at relatively smaller sample sizes. The mean values of α approximated the true values sufficiently when the number of events exceeded 100. The estimated μ values approached the true ones as the event density decreased, accompanied by reduced variance. For 100 and 1,000 event conditions, the median μ estimates fell within the mean of 8,000 event condition ± 3σ range when the event density was below 3.1 and 5.3 events/day, respectively.
- The evaluation of μ variations in geothermal fields, where swarm-like microseismicity frequently occurs, requires appropriate threshold settings of event density within the time window. Therefore, simulation using synthetic catalogs and the time windows is recommended. Thresholds of event density for stable and accurate estimation of μ were derived from such simulations.

CONCLUSION

- As a guideline for real-data analyses:

(1) Perform simulations using synthetic catalogs and time windows to determine the threshold of event densities for stable μ estimation.

(2) In real-data, expand the time window to meet the determined threshold of event density and estimate the temporal variation of μ.

- We propose this as a practical framework for reliable μ estimation in geothermal fields.

REFERENCES

- Ogata Y.: Statistical Models for Earthquake Occurrences and Residual Analysis for Point Processes, *J. Am. Stat. Assoc.*, **83**, (1988), 9-27.
- Hainzl S., Ogata Y. Detecting fluid signals in seismicity data through statistical earthquake modelling, *J. Geophys. Res*, 110 (B5), (2005), B05S07.