Imperial College London

Department of Earth Science and Engineering

MSc in Applied Computational Science and Engineering

Independent Research Project
Project Plan

Forecasting induced seismicity in Oklahoma

by

Zhiyong Liu

zl1220@ic.ac.uk
GitHub login: acse-liuzyon

Supervisors:
Dr. Stephen P. Hicks

July 2021

GitHub repository: https://github.com/acse-2020/acse2020-acse9-projectplan-liuzyon

Abstract

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

1 Introduction

It is well known that humans can cause earthquakes through fluid injection and extraction. Ellsworth stated the understanding of the causes and mechanics of human-induced earthquakes. It includes wastewater injection, emerging oil and gas recovery technologies, and other indirect induced activities, including deep fluid injection (Ellsworth 2013). Such cases of induced seismicity have been recorded and proven in Oklahoma, where seismicity has been increased dramatically since 2010 (Ellsworth 2013). In cases like Oklahoma, because the rate of earthquakes was very low before high-rate wastewater injection, it is relatively easy to determine the fundamental causes of induced seismicity. Therefore, due to the low background stress in intraplate regions, the human triggering signatures are clearly identifiable. However, in tectonically-active areas, it is more challenging to distinfuish between natural and triggered seismicity. In tectonically active regions in the US, such as California, although oil and gas extraction has taken place for many decades, only a handful of studies have been published with a focus on these areas (Hough et al. 2017). In these areas, Big-data and statistical approaches will be crucial in separating natural causes from potential human triggering factors. Hincks et al. developed a Bayesian network to for quantitative evaulation of correlations between well operational parameters, geological formation, and seismicity. The injection depth relative to crystalline basement was found to be the most significant parameter for seismic moment release (Hincks et al. 2018).

Wozniakowska and Eaton performed a machine learning estimation of the seismogenic activation potential for each well using logistic regression and found that the injection depth influence greatly the seismogenic activation potential (Wozniakowska & Eaton 2020). Norbeck and Rubinstein genreated a model based on fluid flow and seismic physics, which associate the past injection trends with the seismicity patterns (Norbeck & Rubinstein 2018).

The correlations of induced earthquakes with fluid extraction and injection are well established. Some physics models are also developed in previous research for earthquake prediction. However, these researches do not explain why seismicity does not always occured close to an injection well. Also, these studies did not develop a statistical model or a machine-learning model to predict earthquakes based on well documented data (such recorded data in Oklahoma)

2 My section

In this work, we implemented code for computing the position of a particle in vertical motion as shown in Fig. 1. The position $y(t)$ at time t we compute using:

$$y(t) = v_0 t - \frac{1}{2}gt^2, \tag{1}$$

where v_0 is the initial velocity, and g is the acceleration due to the Earth's gravity.

The Python code we implemented for computing $y(t)$ is:

```python
def position(t, v0=0, g=9.81):
    """My function."""
    return v0*t - 0.5*g*t**2
```

We made our computational workflows reproducible by employing all benefits of the Jupyter environment (Beg et al. 2021).
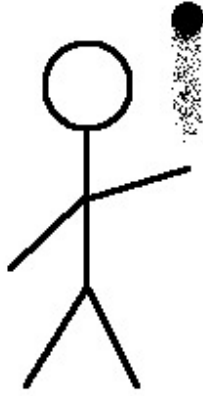
Figure 1: Particle in vertical motion.

Conclusions

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

References

Beg, M., Taka, J., Kluyver, T., Konovalov, A., Ragan-Kelley, M., Thiéry, N. M. & Fangohr, H. (2021), 'Using Jupyter for reproducible scientific workflows', *Computing in Science and Engineering* **23**(2), 36–46.

Ellsworth, W. L. (2013), 'Injection-induced earthquakes', *Science* **341**(6142).

Hincks, T., Aspinall, W., Cooke, R. & Gernon, T. (2018), 'Oklahoma's induced seismicity strongly linked to wastewater injection depth', *Science* **359**(6381), 1251–1255.

Hough, S., Tsai, V., Walker, R. & Aminzadeh, F. (2017), 'Was the mw 7.5 1952 kern county, california, earthquake induced (or triggered)?', *Journal of Seismology* **21**, 1613 – 1621.

Norbeck, J. & Rubinstein, J. L. (2018), 'Hydromechanical earthquake nucleation model forecasts onset, peak, and falling rates of induced seismicity in oklahoma and kansas', *Geophysical Research Letters* **45**(7), 2963–2975.

Wozniakowska, P. & Eaton, D. W. (2020), 'Machine learning-based analysis of geological suscep-
tibility to induced seismicity in the montney formation, canada', *Geophysical Research Letters*
47(22), e2020GL089651.