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Comparison between Utsu's and Vere-Jones' aftershocks model by means of a computer simulation based on the acceptance–rejection sampling of von Neumann

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ABSTRACT

In this research, a new algorithm for generating a stochastic earthquake catalog is presented. The algorithm is based on the acceptance–rejection sampling of von Neumann. The result is a computer simulation of earthquakes based on the calculated statistical properties of each zone. Vere-Jones states that an earthquake sequence can be modeled as a series of random events. This is the model used in the proposed simulation. Contrariwise, Utsu indicates that the mainshocks are special geophysical events. The algorithm has been applied to zones of Chile, China, Spain, Japan, and the USA. This allows classifying the zones according to Vere-Jones' or Utsu's model. The results have been quantified relating the mainshock with the largest aftershock within the next 5 days (which has been named as Bath event). The results show that some zones fit Utsu's model and others Vere-Jones'. Finally, the fraction of seismic events that satisfy certain properties of magnitude and occurrence is analyzed.

1. Introduction

This paper presents a brand new methodology based on Bath's law, Vere-Jones's model, and Utsu's model. An algorithm able to generate an earthquake catalog that satisfies the statistical behavior that any temporal earthquakes series must follow (Gutenberg–Richter law and Poisson's distribution function) is presented. This new algorithm is based on the acceptance–rejection sampling of von Neumann (John von Neumann, 1951).

Two extreme models of aftershocks have been considered. The first one is based on the space-time assumption of random seismic events (Vere-Jones, 1969). The second one considers that there are special geophysical seismic events or mainshocks (Utsu, 1969). Both models identify the mainshock and the largest aftershock of the series (hereinafter Bath event). Vere-Jones (1969) stated that the mainshock and the Bath event are simply the largest earthquake and the second one of a set of identically distributed random variables. These are distributed according to the same Gutenberg and Richter (1954) distribution. This model offers the possibility of creating a seismic catalog randomly generated to compare the validity of Vere-Jones (1969) model. By contrast, Utsu (1969) pointed out that the mainshock is physically different from other events and has a different magnitude distribution. It should be noticed that if a simulation able to generate a seismic catalog based on Utsu's model is pretended, the physical mechanism underlying the mainshock should be known. Vere-Jones (1969) asserted that earthquake generation is due to randomness. Therefore, both models are extreme.

Later, a without precedent criterion that allows measuring the randomness of the earthquake series, based on the comparison between the simulated earthquake series and the real one by means of certain properties of magnitude and temporal scale, is defined. To compare both models, different datasets have been considered. In particular, datasets from Chile, China, Spain, Japan, and the USA have been used. Note that these catalogs have not been intentionally declustered in order to validate the hypotheses stated by Vere-Jones (1969) and Utsu (1969). It is worthy of mention that if the desclustering is made, the Bath event would be eliminated. Thus, the random simulation based on the seismic statistical properties of the zone will let deciding between both models for each zone.

Finally, in the Appendix A, a statistical analysis of the validation of the conclusions is made. Satisfactory results are obtained. This is a

Abbreviations: GR law, Gutenberg–Richter law; MD, magnitude difference; TD, time difference.

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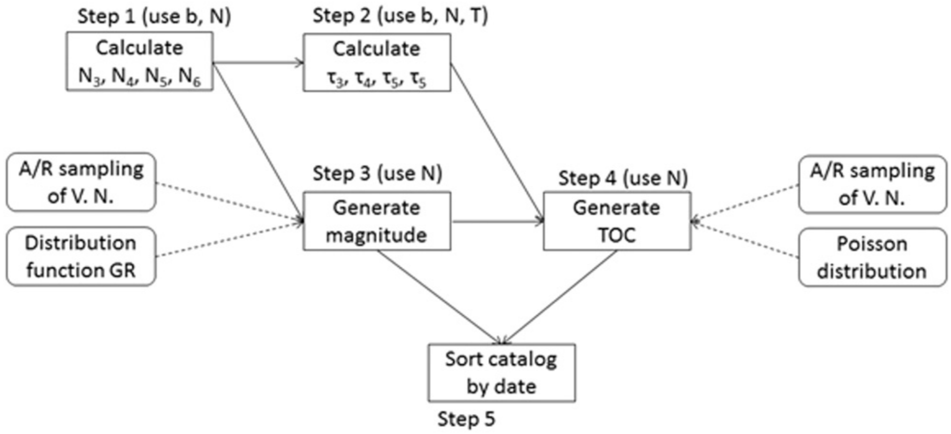

Fig. 1. Flowchart of the proposed algorithm to generate random earthquake catalogs.

great achievement due to the common paradigm that supports that earthquake predictability is close to zero.

To sum up, the research presented in this paper proposes a new stochastic algorithm to generate artificial earthquake catalogs for various seismic zones of the world. For generating an appropriate catalog for every zone, it uses the seismic statistical properties of every zone. This catalog is later used for comparing Utsu's and Vere-Jones' aftershock model. For the first time, both models are compared. Moreover, new variables *Magnitude Difference* and *Time Difference* are used for the comparison.

The remainder of the paper is structured as follows. First, the theoretical fundamentals related to this research are detailed. Second, the underlying geophysical fundamentals are shown. Third, the proposed procedure is explained. Next, the results achieved are reported. A critical discussion on them is summarized. Finally, the conclusions from this research study are drawn.

2. Theoretical fundamentals

2.1. Related works

Utsu (1969) studied the aftershock sequence for shallow earthquakes occurred in and near Japan. This research was a continuation of his previous study of the period 1926–1959 (Utsu, 1961). Mainshocks of M ≥ 6.0 were used for the period 1926–1958 and mainshocks of M ≥ 5.5 in the period 1959–1968. Up to twelve parameters were analyzed. The author concluded that only a mutual correlation was found between the *A* parameter (the area of the aftershock region) and the M_0 (magnitude of the mainshock) and M_1 (magnitude of the largest aftershock) parameters.

Vere-Jones (1969) revisited Bath's law. The author obtained a negative exponential distribution with mean around 0.5 rather than a distribution closely concentrated about 1.2. Moreover, the researcher observed a positive correlation between this magnitude difference and the magnitude of the mainshock. It should be noted that Bath's law predicts a negative or zero correlation. In this study, it was concluded that these results do not match Bath's law. Nevertheless, the researcher pointed out that the discrepancies could be due to the bias introduced by the use of different cutoff magnitudes for the mainshock and the largest aftershock as mentioned by Utsu (1969).

Lombardi (2002) studied the compatibility between the Gutenberg–Richter law and Bath's law. In particular, the author studied the difference between the magnitude of the mainshock and the second larger aftershock. This parameter was named as D_1 in their study. She showed that the distributions of the mainshock, the largest aftershock and D_1, depend on the difference between a second threshold magnitude (larger than the threshold magnitude) and the threshold magnitude and on the number of events in the sequence.

Later, Console et al. (2003) also revisited Bath's law. They also used the D_1 parameter in their study. Their model reported that D_1 is strongly dependent on the magnitude cutoff. The authors concluded that Bath's law and the Gutenberg–Richter law do not fully agree. However, they asserted that this difference is not as great as sometimes was previously stated.

Helmstetter and Sornette (2003) did a research based on Vere-Jones (1969) and Console et al. (2003). For that purpose, the authors used the ETAS model of seismicity. It was concluded that there is a good agreement of the model with Bath's law in a certain range of the model parameters.

The work of Vere-Jones (2008) is revealing as he used a statistical background to conclude that the statistical simulation gave a good match to Bath's law.

In 2012, Shearer studied the magnitude dependence for foreshocks and aftershock in southern California. The author asserted that increased triggering caused by larger earthquakes is compensated by their decreased numbers. The researcher reports that the parameters of these triggering models can be adjusted to fit Bath's law. By contrast, in Shearer's study is also stated that computer simulations of individual triggered sequences show larger variations in the number of aftershocks. Nevertheless, Shearer's research is centered on the study on the foreshock-aftershock ratio.

Console et al., 2015 generated a synthetic earthquake catalog for the Corinth Gulf fault system (Greece). The work is based on time-dependent modeling of earthquake recurrence on major faults. The algorithm considers an average slip rate released by earthquakes to each one of the segments of the fault system. The frequency magnitude distribution of their catalog is consistent with the real registers. Hence, the model proposed by the author is deterministic. By contrast, the algorithm proposed in this work is stochastic.

Siriki et al. (2015) presented a stochastic source-model-generation algorithm. It generates stochastic source models for large magnitude strike-slip earthquakes. It is based on the combination of fault ruptures

Table 1
Parameters for Pichilemu obtained from the real and the simulated data.

Real						Simulated					
Mag	MD	MDSD	TD	TDSD	F_1	Mag	MD	MDSD	TD	TDSD	F_1
4.0	0.28	0.21	1.80	1.54	91%	4.0	0.52	0.31	2.52	1.48	26%
4.5	0.29	0.28	1.79	1.61	96%	4.5	0.87	0.43	2.47	1.43	44%
5.0	0.44	0.37	1.53	1.54	98%	5.0	1.31	0.46	2.70	1.60	36%
5.5	0.59	0.70	2.26	1.61	100%	5.5	1.74	0.53	2.90	1.50	40%
6.0	0.46	0.35	1.45	1.43	100%	6.0	2.19	0.28	1.87	1.32	33%