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Bayesian analysis on earthquake magnitude related to an active fault in Taiwan

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ABSTRACT

It is understood that sample size could be an issue in earthquake statistical studies, causing the best estimate being too deterministic or less representative derived from limited statistics from observation. Like many Bayesian analyses and estimates, this study shows another novel application of the Bayesian approach to earthquake engineering, using prior data to help compensate the limited observation for the target problem to estimate the magnitude of the recurring Meishan earthquake in central Taiwan. With the Bayesian algorithms developed, the Bayesian analysis suggests that the next major event induced by the Meishan fault in central Taiwan should be in M_w 6.44 $\pm$ 0.33, based on one magnitude observation of M_w 6.4 from the last event, along with the prior data including fault length of 14 km, rupture width of 15 km, rupture area of 216 km^2, average displacement of 0.7 m, slip rate of 6 mm/yr, and five earthquake empirical models.

1. Introduction

The region around Taiwan is known for high seismicity, not to mention a catastrophic event like the M_w 7.6 Chi–Chi earthquake could recur in decades [1]. Recently, there are studies suggesting that the return period of a major earthquake induced by the Meishan fault in central Taiwan might be as short as 160 years, not to mention the very last Meishan earthquake in 1906 was occurring more than one hundred years ago. Under the circumstances, the risk of the active fault inducing a major earthquake in near future is considered relatively high, and the subject has been discussed in several recent studies [2,3]. Therefore, from a different perspective with new methodology, the target problem of this study is to evaluate the magnitude of the next Meishan earthquake in central Taiwan that could occur in near future given its short return period. More introductions to the background of the Meishan fault in central Taiwan are given in one of the following sections.

One possibility to evaluate such a problem is via statistical study. But on the other hand, it is understood that sample size is important to statistical assessments and inferences. For example, given an active fault is known for inducing a major earthquake in M_w 6.5 (moment magnitude), a best estimate on the magnitude of the next recurrence will be exactly the same size as the observation, although it is less representative based on one magnitude observation only. Unfortunately, this is the same situation for the target problem of the study, aiming to evaluate the magnitude of the next Meishan earthquake but with only one magnitude observation available for the analysis.

In contrast to statistics-based methods, the Bayesian inference is a relatively new approach that is more useful for evaluating a problem with very limited observations. Basically, the Bayesian approach is to use other sources of data to compensate limited statistics, helping develop a new Bayesian estimate by integrating multiple sources/types of data, usually referred to as prior and observation.

The Bayesian approach has been increasingly applied to many different studies to develop a new estimate from multiple sources of data e.g., [4–6]. In earthquake engineering and engineering seismology, an early study can be dated back to the 1960s [7], introducing the framework of the Bayesian calculation for seismology research. More recently, several other Bayesian methods for earthquake studies were reported, such as the application to earthquake early warning [8,9], tectonic stress evaluation [10], and earthquake catalog characterizations [11], among others [12,14].

Although many different applications were reported, the underlying motivation of the Bayesian studies is the same: Integrating multiple sources/types of data to evaluate or re-evaluate a problem, rather than only relying on (limited) statistics from observation. Take

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those studies above for example, the framework of Bayesian earthquake early warning is to utilize some empirical models to compensate the limited data at the initial stage of earthquake, for estimating its magnitude and location more reliably on a real-time basis [8,9]. On the other hand, a Bayesian algorithm [11] to evaluate the completeness magnitude (M_c) of an earthquake catalog is facilitated with the prior data in proximity regions, then integrated with the locally observed seismicity. Note that such a Bayesian calculation is similar to a later application to estimate earthquake rates (or frequencies) around a study area, also using the data from proximity areas as priors [14]. Other recent Bayesian applications to earthquake studies include the probability assessment on earthquake-induced landslides [31], evaluation of the source parameters of a major earthquake [32], and structure safety analysis under earthquake condition [33]. Similarly, new Bayesian methods are increasingly developed for other problems [34–36].

As a result, given the short return period reported, the key scope of the study is to evaluate the magnitude of the next major earthquake induced by the Meishan fault in central Taiwan, on the basis of a novel Bayesian calculation integrating multiple sources/types of data to compensate the lack of adequate statistics from observation. In this study, we first derived a new Bayesian algorithm for evaluating earthquake magnitude distributions related to an active fault, based on both observational and prior data. Next, we applied the methodology to the target problem, showing there should be a 10% probability for the next Meishan earthquake in central Taiwan to exceed M_w 6.9, considering one magnitude observation of M_w 6.4 from the last Meishan earthquake, and the prior data including fault length of 14 km, rupture width of 15 km, rupture area of 216 km^2, average displacement of 0.7 m, slip rate of 6 mm/yr, and five earthquake empirical models.

The paper is organized with an overview of the Bayesian approach, followed by the introductions to the Meishan fault in central Taiwan. Next, the observation and prior data for this Bayesian study were introduced and summarized, followed by the developments of the new Bayesian algorithm, and the Bayesian inference to the magnitude of the next Meishan earthquake from the multiple sources/types of data.

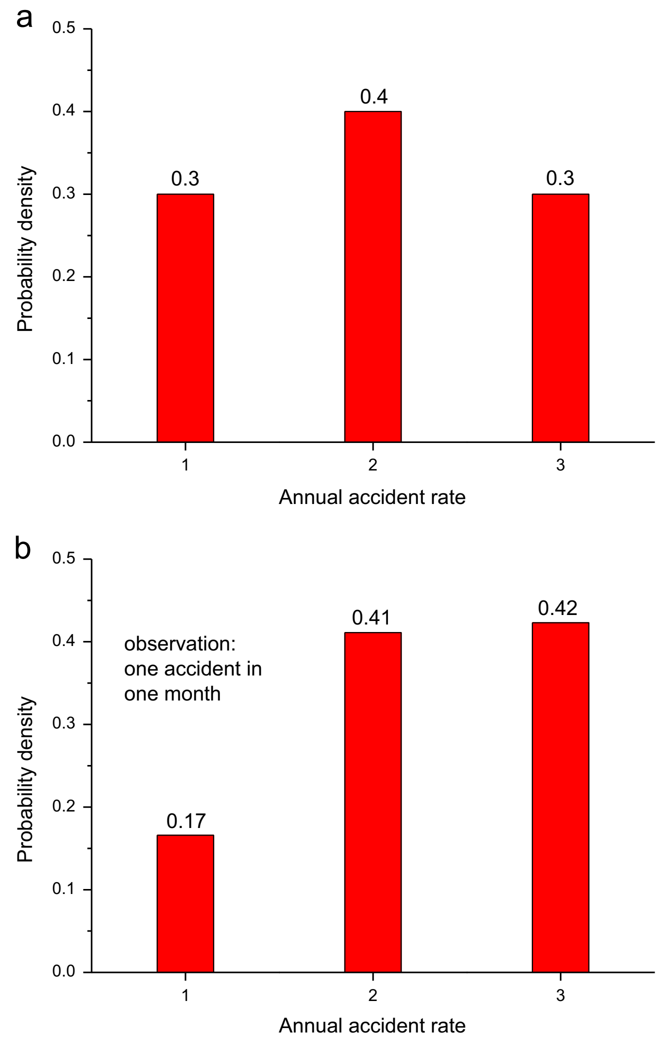

Fig. 1. A demonstration example to the Bayesian approach: (a) the prior information or the prior probability mass function, and (b) the posterior integrating the prior with the observation [1].

2. Overview of the Bayesian approach

2.1. The algorithm

As mentioned previously, the Bayesian approach is to integrate prior information with (limited) observation to develop a new estimate, which is different from the one relying on samples or statistics only. To further illustrate the method, we summarized an example from the literature as follows [15]: Fig. 1a shows the prior information or the so-called prior probability mass function about the accident at a given cross road, suggesting the mean rate equal to two accidents per year. It is worth noting that because this example is a discrete case, its probability function is specifically referred to as probability mass function (PMF), in contrast to probability density function (PDF) that is used for describing the probability function of a continuous random variable [15]. Nevertheless, the two basically refer to the same thing in probability and statistics.

On the other hand, given the total number of accidents equal to one observed in an arbitrary month, the accident rate should be 12 per year from the observation. Note that although the reference only mentions "one accident observed in one month" in the description to the example [15], the description should explicitly imply the one-month observation was conducted in an arbitrary period of 30 (or 31) days in a row. Therefore, in this paper we refer to such a description or the observation as "one-accident-in-one-arbitrary-month" in the following.

In addition to the two estimates from observation or prior, the third one is the Bayesian estimate by integrating the two. For a discrete case like this demonstration example, the underlying algorithm of the Bayesian approach can be expressed as follows [15]:

$$P''(\theta_i) = \frac{P'(\theta_i) \times P(\varepsilon|\theta_i)}{\sum_{i=1}^{n} P'(\theta_i) \times P(\varepsilon|\theta_i)} \tag{1}$$

where ε denotes observation, $P'(\theta_i)$and$P''(\theta_i)$are prior and posterior probabilities for each prior estimate θ_i, and $P(\varepsilon|\theta_i)$ is the likelihood function, or the probability for observation ε to occur given θ_i.

Understandably, θ_i, $P'(\theta_i)$, and ε are the given data in a Bayesian calculation. (For this demonstration example, θ_i are 1 or 2 or 3 accidents, $P'(\theta_i)$ are 30% or 40% or 30%, and ε is the "one-accident-in-one-arbitrary-month" observation.) By contrast, $P(\varepsilon|\theta_i)$ and $P''(\theta_i)$ are unknowns that we want to calculate during the Bayesian analysis. More importantly, from the unique algorithm given in Eq. (1), we can see how the Bayesian approach integrates prior data and observation with the well-established algorithm.

It is worth noting that in the calculation of the likelihood function $P(\varepsilon|\theta_i)$, we need to know (or assume) what kind of probability distributions the target random variable should be following. That is, in this demonstration example, the accident rate is considered following the Poisson distribution, with its probability mass function