SCIENCE CHINA
Earth Sciences

•REVIEW•

https://doi.org/10.1007/s11430-021-9824-0

Application and discussion of statistical seismology in probabilistic seismic hazard assessment studies

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Received March 28, 2021; revised July 3, 2021; accepted July 27, 2021; published online October 13, 2021

Abstract Earthquakes are one of the natural disasters that pose a major threat to human lives and property. Earthquake prediction propels the construction and development of modern seismology; however, current deterministic earthquake prediction is limited by numerous difficulties. Identifying the temporal and spatial statistical characteristics of earthquake occurrences and constructing earthquake risk statistical prediction models have become significant; particularly for evaluating earthquake risks and addressing seismic planning requirements such as the design of cities and lifeline projects based on the obtained insight. Since the 21st century, the occurrence of a series of strong earthquakes represented by the Wenchuan $M8$ earthquake in 2008 in certain low-risk prediction areas has caused seismologists to reflect on traditional seismic hazard assessment globally. This article briefly reviews the development of statistical seismology, emphatically analyzes the research results and existing problems of statistical seismology in seismic hazard assessment, and discusses the direction of its development. The analysis shows that the seismic hazard assessment based on modern earthquake catalogues in most regions should be effective. Particularly, the application of seismic hazard assessment based on ETAS (epidemic type aftershock sequence) should be the easiest and most effective method for the compilation of seismic hazard maps in large urban agglomeration areas and low seismic hazard areas with thick sedimentary zones.

Keywords Statistical seismology, Earthquake prediction, Probabilistic seismic hazard assessment, Stress release model, Epidemic type aftershock sequence model

Citation: Pei W, Zhou S, Zhuang J, Xiong Z, Piao J. 2021. Application and discussion of statistical seismology in probabilistic seismic hazard assessment studies. Science China Earth Sciences, 64, https://doi.org/10.1007/s11430-021-9824-0

1. Introduction

China suffers the greatest damage from earthquakes worldwide. When accurate earthquake prediction cannot be achieved, the incorporation of seismic design into urban building design and lifeline engineering is considered to be one of the measures for mitigating earthquake disasters. This is actually the main aspect of earthquake engineering (Hu, 1988). The main role of seismologists is to predict the risk (probability) of strong earthquakes and calculate or forecast the strong ground motion produced by strong earthquakes in certain areas or fault zones (Zhang et al., 2008, 2012; Zhang et al., 2017b). The aforementioned method of earthquake prediction differs significantly different from the three-element (time, location, and magnitude) prediction of earthquakes in the monitored area in this study's objectives and methods. The goal is to determine at the design stage how high the seismic strength of the building should be. This addresses the probability of the building being subjected to an earthquake exceeding a certain magnitude during its service life (usually several decades or a hundred years). We discuss long-term earthquake prediction or probabilistic seismic hazard assessment on the scale of decades or a

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hundred years. In contrast with extracting "precursor" phenomena or prediction indicators based on the summary of earthquake cases (Shi et al., 2001; Chen, 2009; Chen, 2010), the aforementioned method is based on long-term seismicity observations in the study area, identified laws of temporal and spatial evolution, establishment of statistical prediction models, and calculation of the probability of earthquakes exceeding a certain magnitude. Considering the stationary Poisson model, which is widely used in earthquake hazard assessment (Gao, 2015) as an example, through long-term seismicity analysis of the study area or fault zone, if the annual occurrence rate above a certain level is λ, then the respective probability density function and cumulative probability distribution function of the waiting time to the subsequent strong earthquake are expressed as follows:

$$\begin{cases} f(\tau) = \lambda \cdot \mathrm{e}^{-\lambda\tau}, \\ F(\tau) = \int_0^\tau f(x)\mathrm{d}x = 1 - \mathrm{e}^{-\lambda\tau}. \end{cases} \tag{1}$$

The first formula is the probability density function of the time interval between events of the stationary Poisson model, and the subsequent formula is the calculation formula for the probability of strong earthquake occurrence within the time window τ.

Eq. (1) shows that the probability of a strong earthquake exceeding a certain magnitude has nothing to do with the starting time in a given area over the succeeding few decades (or a hundred years). This earthquake hazard prediction model is a type of time-independent model of earthquake hazard prediction. "Time-independent" in this case means that the calculated probability of a strong earthquake has nothing to do with the start time.

Since the 21st century, following the rapid economic growth in countries represented by China, urbanization worldwide is constantly growing. Meanwhile, the need for precise earthquake hazard prediction has continually increased. Deterministic earthquake prediction based on physical models depends on a clear understanding of the seismogenic process and the ability to express the dynamic process of the seismic source using stringent mathematical and physics equations. Additionally, it presupposes that the "crust imaging" model that monitors the regional structure, physical properties and states is conditional on the real-time four-dimensional data of the key precursor and earthquakes in the study area, and is ultimately accomplished through the processing of massive data as well as the calculation and simulation of the earthquake initiation process on the high-performance computing platform (Shi et al., 2018). However, the above-mentioned foundations and premises have not been accomplished so far, and will not be for a long time. In contrast, the development of the seismology theory has also promoted the update and development of seismic hazard assessment methods. Many time-dependent seismic hazard prediction models that are more reasonable than the stationary Poisson model have been proposed. This article first briefly summarizes the development of statistical seismology, and then focuses on analyzing the research results and existing challenges of statistical seismology in seismic hazard prediction. Finally, the development direction of statistical seismology is discussed in the hope of introducing new related theories and developments into long-term earthquake hazard assessment and earthquake engineering research to promote the rapid development of research in related fields in China in a new historical stage in the future.

2. Development of statistical seismology and seismic hazard assessment

Since the establishment of its modern version in the early 20th century, seismology has been closely related to the key development of statistics. The aim of developing this practice was to extract useful information from huge amounts of data. Statistical seismology has now become an important part of seismology. In 1995, Vere-Jones (2001) taught a course on a statistical analysis of seismic activity at the Graduate School of the Chinese Academy of Sciences, and named it statistical seismology following a suggestion by academician Shi Yaolin. To date, this subject is an important branch of seismology, providing the basic theories and technical mechanism of seismic activity analysis, and combining tectonics/geodynamics and traditional seismology dominated by seismic waveform analysis.

2.1 Brief introduction and development of typical earthquake statistical relations

In 1982, John Milne, James Ewing, and Thomas Cray installed the first modern seismometer in Japan, marking the beginning of modern seismology (Zhou and Xu, 2018). Seismometers allowed for the detection of the occurrence of global earthquakes making it possible to calculate their occurrence time and hypocenter locations, and compile relatively complete earthquake catalogs. The main applications of statistics in earthquake studies during this period are simple statistical techniques such as linear regression and point estimation sparsely applied in individual studies on different topics. Among them, the Omori-Utsu formula and magnitude-frequency relationship have the greatest influence and have been used extensively in seismic hazard prediction.

The empirical statistical formula for the magnitude-frequency relationship (also known as the G-R law; Gutenberg and Richter, 1942) is proposed based on the analysis and study of the California earthquake catalog by Gutenberg and Richter in 1942.

$$\log N(M) = \mathrm{a} - \mathrm{b}M, \tag{2}$$

where a and b are constants, and $N(M)$ is the number of earthquakes whose magnitudes at least equal to M. That is, the number of earthquakes increases by 10^b times when the magnitude decreasing by one. Usually, the value of b is approximately 1. In 1945, Gutenberg and Richter proposed the G-R relationship with an upper truncated magnitude limit. Later, seismologists from various countries proposed many empirical scaling laws related to the earthquake magnitude, in an attempt to solve the discrepancies in low and high magnitude range to fit the above-mentioned relationship. Twelve magnitude-frequency relations, which consider fractal theory, self-organized criticality, statistical physics, and information entropy, including several nonlinear magnitude-frequency relationships, have been derived from 1971 to 1991 (IASPEI Software, see Utsu and Ogata, 1997). However, the G-R law expressed in eq. (2) is still the most recognized and widely used magnitude-frequency scaling law so far.

For the discrepancy in low-magnitude, when the actual earthquake catalog is fitted with the Gutenberg-Richter magnitude-frequency relationship, the usual explanation is the omission of the low-magnitude detection of the seismic network. The discrepancy in high-magnitude is well theoretically explained by Academician Chen Xiaofei's research team in their study of rupture dynamics (Zhang and Chen, 2006; Xu et al., 2015; Zhang et al., 2017a). These studies report that the magnitude frequency of large earthquakes with magnitudes exceeding 6.5 is more likely to depend on the characteristic scale distribution of seismogenic faults in the source area.

In his study of the aftershocks of the 1891 M_S8.0 Nobi earthquake, Omori (1894) found that the number of aftershocks occurring each day can be adequately expressed using the following equation:

$$n(t) = \mathrm{K} / (t + \mathrm{c}), \tag{3}$$

where t is the time from the occurrence of the main shock, and K and c are constants.

After studying the aftershocks of many earthquakes, Utsu (1961) believed that the decay of aftershock numbers could occur faster than presented in the Omori formula, and proposed the modified Omori formula:

$$n(t) = \mathrm{K} / (t + \mathrm{c})^P. \tag{4}$$

Utsu et al. (1995) successively applied the sum of the modified Omori formula to express the frequency of sequences containing high-order aftershocks. This also indicates that the aftershock sequence is a combination of aftershock activities caused by the main shock and high-order aftershock activities caused by strong aftershocks. The modified Omori formula expressed in eq. (4) plays an important role in the prediction of aftershocks. Based on the Omori-Utsu formula, Liu et al. (1979) and Liu and Kong (1986) suggested the use of the aftershock decay coefficient h as an index to determine the characteristics of earthquake sequences for short-term hazard assessment.

2.2 Time-independent model of earthquake hazard prediction (point process model)

In the 1970s, the introduction of the point process model into the study of earthquake risk prediction began. This development is also required in earthquake engineering. The building code required that the probability of suffering a certain peak-ground-acceleration in the coming contain years be mandatorily considered in the design of building structures; that is, the probability of a nearby large earthquake at a certain level. In earthquake engineering, the stationary Poisson model was often used to estimate the future earthquake hazard. In this model, according to the average earthquake occurrence rate λ in the study area, the probability of strong earthquakes above a certain magnitude in a given area over the subsequent few decades (or 100 years) is calculated. The calculation result has nothing to do with the starting point of the calculation time. This type of earthquake hazard prediction model is classified under the time-independent model of earthquake hazard prediction. The Working Group on California Earthquake Probabilities (1988) used the concept of a time-dependent model when estimating the probability of a large earthquake on the San Andreas fault, which is an update process in mathematics. Vere-Jones (1970, 1973, 1975) proposed the use of conditional intensity to determine the point process model describing the occurrence of an earthquake. The definition of conditional intensity is the expectation of future earthquake occurrence based on the given observation information (historical information of earthquake process and/or certain external observations),

$$\begin{aligned}\lambda(t) = \lim_{\Delta t \downarrow 0} \frac{1}{\Delta t} \Pr\{&\text{earthquake occured in} \\ &[t, t + \Delta t) | \text{ past observation}\}.\end{aligned} \tag{5}$$

Based on the elastic rebound theory (Reid, 1910) and using the random point process theory in statistics, Vere-Jones (1978) proposed a time-dependent earthquake hazard prediction model referred to as the stress release model (SRM). The basic concept is the assumption that the occurrence rate of earthquakes in a certain area is related to the stress level in that area. The stress level in a given area gradually builds up owing to tectonic movement loads, and decreases suddenly coinciding with earthquakes. Therefore, the calculation of the probability of future earthquake occurrence in a given area should be based on the nonstationary Poisson model, and the earthquake occurrence rate λ can be expressed as follows:

$$\lambda(t) = e^{\nu X(t)}, \tag{6}$$

where $X(t)$ is the stress level at time t in a given area, and ν is the correlation coefficient between stress and seismicity. $X(t)$ can be expressed as follows:

$$X(t) = X(0) + \rho t - S(t), \tag{7}$$

where $X(0)$ is the initial stress level, ρ is the constant loading rate, and $S(t)$ is the accumulated stress released from earthquakes in period $[0, t]$.

Moreover, Ogata (1988) introduced the idea of the branching process into the Omori formula, assuming that each event, regardless of its size, can in principle trigger its own offspring. This new model is called the epidemic type aftershock sequence model (ETAS). The temporal conditional intensity of this model is expressed as follows:

$$\lambda(t) = \mu + \sum_{i:t_i<t} Ke^{\alpha m_i} / (t - t_i + c)^p. \tag{8}$$

The SRM and ETAS have since been expanded and developed. To address the limitation posed by SRM being only suitable for single-fault seismic hazard estimation, Liu et al. (1999a) proposed the coupled stress release model (CSRM), and Jiang et al. (2011) proposed the multidimensional stress release model (MSRM). The MSRM has greatly improved the SRM, making it a spatiotemporal seismic hazard statistical prediction model that can be used in the calculation of probabilistic seismic hazard in complex structural areas. Another important development is the incorporation of rate- and state-dependent friction law into the ETAS model to explain various phenomena in microseismicity (Stein, 1999; Dieterich et al., 2000), thus significantly improving the influence and application of the ETAS model. So far, the SRM and ETAS models have become the mainstream models used to estimate long- and short-term seismicity and carry out seismic hazard prediction. In addition to the traditional time-independent and time-dependent models (Field et al., 2014, 2015), the third Uniform California earthquake rupture forecast (UCERF-3) provided by the Working Group on California Earthquake Probabilities also includes the UCERF3-ETAS model (Field et al., 2017), which performs operational earthquake prediction (Jordan and Jones, 2010). In the global earthquake model project (GEM, https://www.globalquakemodel.org/) launched in 2006, seismic activity prediction is regarded as the most important part of the probability seismic hazard assessment (PSHA). GEM has also begun to use time-dependent models (Woessner et al., 2015).

However, for earthquake prediction on time scales of one year, several months or less (called short-term predictions), identifying effective earthquake prediction methods is one of the important topics explored by seismologists (Jia et al., 2012, 2014, 2018). A newly developed method requires rigorous statistical tests. Particularly, probability gain has become the basic measurement standard for comparing the prediction results of statistical models (Aki, 1981; Feng et al., 1981; Hamada, 1983; Chen and Ma, 1990). The international project "collaboratory for study of earthquake predictability (CSEP)" was set up by the Southern California Earthquake Center and had started rigorous statistical testing for submitted earthquake forecasting methods or models. Japan, Europe, New Zealand, and China also installed their own CSEP projects, indicating that statistical seismology is now more widely and significantly applied in earthquake prediction research.

3. Typical seismic hazard prediction models considering North China as an example

North China is densely populated, and economically developed, and has suffered extensive damage from large earthquakes. Numerous large earthquakes, including the Xingtai Earthquake (1966, M_S7.2), the Bohai Earthquake (1969, M_S7.4), the Haicheng Earthquake (1975, M_S7.3), the Tangshan earthquake (1976, M_S7.8), the Luanxian earthquake (1976, M7.1), the Baotou earthquake (1996, M6.4), and the Zhangbei earthquake (1998, M6.2) have occurred in North China since the 1960s (Figure 1). These earthquakes resulted in heavy casualties and large economic losses. Therefore, the earthquake hazard prediction in North China has always garnered unique attention from seismologists in China. Considering North China as an example, we analyzed the widely used seismic hazard prediction models in succession.

3.1 Identification of potential source area and earthquake hazard prediction

The potential source area refers to the fault segment or area where destructive earthquakes may occur in the future. The identification of the potential source area includes the range (boundary) of the potential source area, the direction of rupture, and the upper limit of the magnitude. The identification of the potential source area is based on the comprehensive seismic geological survey and historical seismic data, and mainly based on the following two principles (Gao and Lu, 2006; Tang et al., 2010):

(1) Earthquake repetition. Large earthquakes may recur in situ in a certain structural location or section, that is, in a section or area where strong earthquakes occurred previously, earthquakes of similar or higher magnitude may occur in the future.

(2) The analogy of seismic structure. Areas or sections with seismic structural characteristics that are similar to those of areas where strong earthquakes have happened may record earthquakes of the same magnitude. In other words, by comparing structural conditions that have not yet yielded large earthquakes with those that have (including ancient

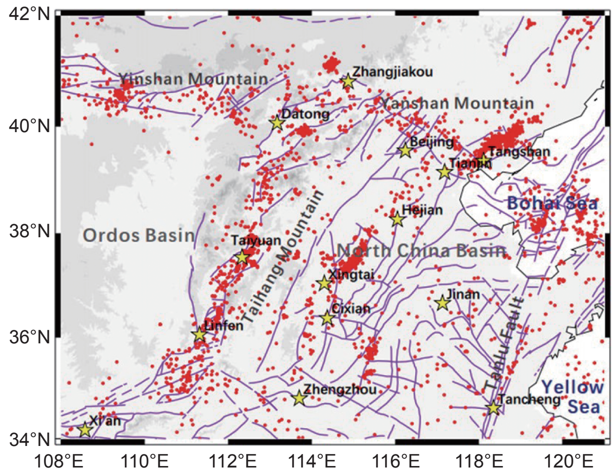

Figure 1 Distribution of faults and modern seismic activities in North China. The purple lines indicate the distribution of faults, the red dots indicate the location of the earthquake epicenter (from January 1, 1980 to December 31, 2016, $M\geq3.0$), and the yellow stars represent the main cities in this area.

earthquake relics), we could determine the possibility of an earthquake of a certain magnitude under certain structural conditions.

The probabilistic seismic hazard assessment carried out in Chinese earthquake engineering is mainly adherent to the method proposed by Cornell (1968) (Gao, 2015). In the PSHA proposed by Cornell (1968), the basic assumptions of the seismicity model in the potential source area are as follows. (1) The seismicity in the same potential source area stabilizes over time and is uniformly distributed. That is, the occurrence patterns of earthquakes in the same potential source area adhere to a particular stationary Poisson model temporally and spatially. (2) The magnitude distribution of earthquakes in the potential source area is adherent to the Gutenberg-Richter relationship described in eq. (2) (G-R law).

An improved PSHA called the Chinese probabilistic seismic hazard assessment (CPSHA) has been used in the compilation of the national seismic zoning map of China in Chinese earthquake engineering since 1990. The assumptions made in the CPSHA method for the seismicity model are as follows (Gao, 2015):

(1) The magnitude distribution of earthquakes in the seismic statistical zone satisfies the G-R relationship with an upper truncated magnitude limit (Xu and Gao, 2012); (2) The occurrence time of earthquakes in the seismic statistical zone satisfies the stationary Poisson model; (3) In the seismic statistical zone, the seismic activity is unevenly distributed among different potential source areas, but uniformly distributed in the same potential source area.

CPSHA is based on the above three hypotheses to establish the corresponding seismic hazard prediction model in each identified potential source area. The specific method is exhaustively described in the "the Publicity Teaching Material of China Earthquake Parameter Zoning Map (in Chinese)" edited by Gao (2015).

Although the above-mentioned probabilistic seismic hazard assessment based on the potential source area has played an important role in the long-term prediction of strong earthquake hazards and the study of earthquake engineering zoning, which is still the mainstream method for the compilation of seismic zoning maps in China. However, this method used for more than half a century has recently been questioned (Stein et al., 2012; Wang, 2012; Wang et al., 2016; Mulargia et al., 2017), owing to the following main flaws.

(1) The correct identification of the potential source area and the estimation of the maximum magnitude are important bases for the effectiveness of the PSHA and CPSHA methods. However, the identification of the potential source area based on historical seismic data and the seismic geological survey of active faults is associated with huge uncertainty because of the omission of historical seismic data and source parameters (such as location and magnitude). A seismic geological survey that is heavily dependent on the empirical knowledge of the researchers is very subjective. All of these will inevitably result in the oversight or significant underestimation of the seismic hazard of certain potential seismic source areas. For example, the Tangshan $M7.8$ earthquake in 1976 and the Wenchuan $M8.0$ earthquake in 2008 accidentally occurred in the low seismic hazard regions and areas with low seismic fortification intensity, causing heavy casualties and massive property losses. A typical foreign example is the $M_W6.2$ Darfield earthquake near Christchurch, New Zealand, on September 10, 2010, which also occurred in low seismic -hazard regions and areas with low seismic fortification intensity, resulting in the death of 185 people and an economic loss of 4 trillion New Zealand dollars.

(2) As the recurrence period of strong earthquakes is one hundred years or even thousands of years, estimating the average occurrence rate λ of strong earthquakes (the number of earthquakes above a certain magnitude per unit time) based on historical seismic data is difficult. Based on the modern earthquake catalog, using the G-R law to calculate the average occurrence rate λ of strong earthquakes from that of small earthquakes is a common solution to this problem. Nevertheless, the discrepancy in high magnitude range to fit the G-R law (Xu et al., 2015; Zhang et al., 2017a) causes large deviations in the calculation of the average occurrence rate of strong earthquakes from that of small earthquakes, causing the probability calculation of earthquake hazard based on the Poisson model Larger uncertainty.

(3) The elastic rebound theory (Reid, 1910) tells us that the occurrence of an earthquake is the result of the stress accumulation on the fault plane exceeding the rupture strength. This shows that the occurrence of earthquakes is not entirely random. Considering the stress accumulation state of the study area, the time-dependent model may be more optimized than the stationary Poisson model.

3.2 Probabilistic seismic hazard assessment based on modern earthquake catalogs

Compared with historical earthquake catalogs or other data, modern earthquake catalogs can guarantee more reliable, complete, and sufficient data. Owing to the lack of empirical identification and setting of potential sources, the probabilistic seismic hazard assessment based on modern earthquake catalogs is simple and yields relatively more objective results.

The first challenge in seismic hazard estimation is the establishment of seismicity models. In the long-term seismicity models, the stationary Poisson model expressed by eq. (1) is the most commonly used in the time domain; the spatial distribution function of earthquakes is usually obtained from the spatial distribution map of earthquakes in the spatial domain (Ogata et al., 1991; Kagan, 1991; Vere-Jones, 1992; Frankel, 1995; Woo, 1996; Jackson and Kagan, 1999). Among them, the kernel estimation method has been the most widely used. Vere-Jones (1992) first applied Gaussian and IBQ (inverse-biquadratic) kernels to calculate seismicity; Frankel (1995) used point sources for seismic hazard analysis and Gaussian kernels with different bandwidths for spatial smoothing. Cao et al. (1996), based on Frankel's method, simplified the hazard calculation using only historical seismic records, and used a power-law smoothing function for smoothing. Woo (1996) also used a power-law smoothing function to calculate seismicity. Jackson and Kagan (1999) used the bimodal directional kernel function based on the IBQ kernel to calculate seismicity. These methods all use a fixed global bandwidth.

In kernel function estimation, if the spatial distribution of earthquakes in the study area is unevenly distributed, the use of a fixed global bandwidth to reflect the characteristics of the entire study area is difficult. A small bandwidth may produce noise estimates (under-smoothing) in sparse seismic regions, while a large bandwidth may cause fuzzy estimates of local seismicity (over-smoothing). To solve this problem, Stock and Smith (2002), Zhuang et al. (2002), and Jiang et al. (2011) proposed an adaptive bandwidth kernel estimation method. The adaptive bandwidth kernel estimation can reflect the spatial inhomogeneity of earthquakes better than the fixed bandwidth kernel estimation, and avoid the over-smoothing or under-smoothing of regional seismic activity.

In addition to the kernel estimation method, the tessellation method is also used to calculate the spatial distribution of seismic activity. For instance, Ogata et al. (2003) used the Delaunay tessellation based Bayesian smoothing (ODTB) method to calculate the spatial occurrence rate of earthquakes. Because the ODTB method is complex and inclined to statistical calculation, Xiong et al. (2019) proposed a simpler incomplete centroidal Voronoi tessellation (ICVT) method based on space tessellation. In this new method, Voronoi segmentation (Okabe et al., 1992) is used to grid the study area, and certain centralization steps are used to reduce the area difference between adjacent grids. This kind of cutting is relatively more conducive to reflecting the spatial distribution characteristics of earthquakes. Considering the seismicity model in North China as an example, we briefly introduce the ICVT method.

Voronoi tessellation (also known as Dirichlet tessellation) was proposed by the Russian mathematician George Fedoseevich Voronoi in 1908. Voronoi tessellation managed to divide the plane into different polygons based on a set of specific points to ensure each polygon contained only one specific point and any location in the polygon was in closer proximity to the specific point than to other points (Tran et al., 2009). From the epicenter distribution, the entire study area is divided into the form shown in Figure 2a using Voronoi tessellation.

In Figure 2a, the data set of the earthquake epicenter location is represented by $\{(x_i, y_i), i=1,\ldots,N\}$, where N represents the number of earthquake events. After tessellation, the earthquake occurrence rate at the epicenter is expressed as follows:

$$\lambda(x_i, y_i) = \frac{1}{TS_i}, \tag{9}$$

where T is the time scale of the seismic data set, and S_i is the area of the ith Voronoi polygon. The remaining points in the area are calculated by triangular linear interpolation. Therefore, the seismicity rate distribution in the study area can be obtained as shown in Figure 2b.

Figure 2b depicts the distribution of earthquake hazards above magnitude 3 in the study area in detail. Based on Figure 2b, substituting the stationary Poisson model, we can also use the methods and principles of SHA or CSHA to further obtain the probabilistic seismic hazard assessment or ground motion parameter zoning map of the study area.

In fact, only moderate earthquakes (such as magnitude 5) and above are significantly destructive. In engineering seismology, our concern is the hazard prediction of moderate earthquakes. Because the higher the magnitude, the fewer the earthquake records, obtaining the detailed earthquake hazard prediction map shown in Figure 2b, based on the high-magnitude earthquake catalog, is difficult. This problem is usually solved by calculating the *b*-value spatial distribution map (Figure 3a) of the study area, and using the G-R law extrapolation method to obtain the seismic hazard prediction map of moderate or large earthquakes as Figure 3b (Chen et al., 1998; Liu et al., 1999b).

3.3 Probabilistic seismic hazard assessment based on stress release model

Owing to its simplicity and convenience, the stationary

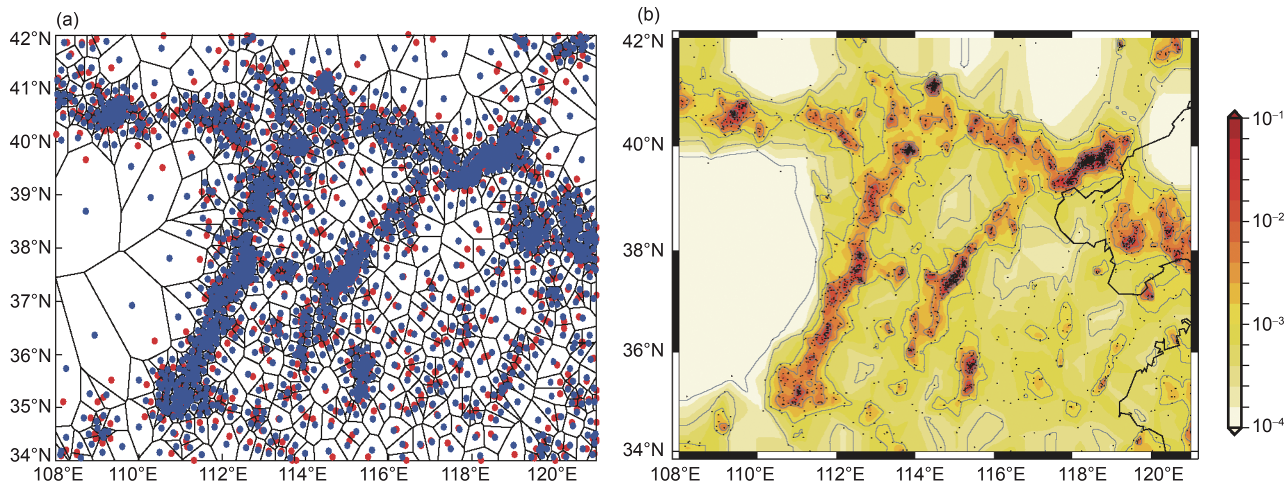

Figure 2 Result of Voronoi tessellation and the seismicity rate distribution map larger than 3 in the study area. (a) Voronoi tessellation of north China, the red dot represents the epicenter location (from January 1, 1980 to December 31, 2016, $M\geq3.0$), and the blue dot is the centroid of the Voronoi polygon; (b) the seismicity rate distribution map above magnitude 3 of North China (unit: events year^{-1} degree^{-2}), and the black dot represents the epicenter location according to Xiong et al. (2019).

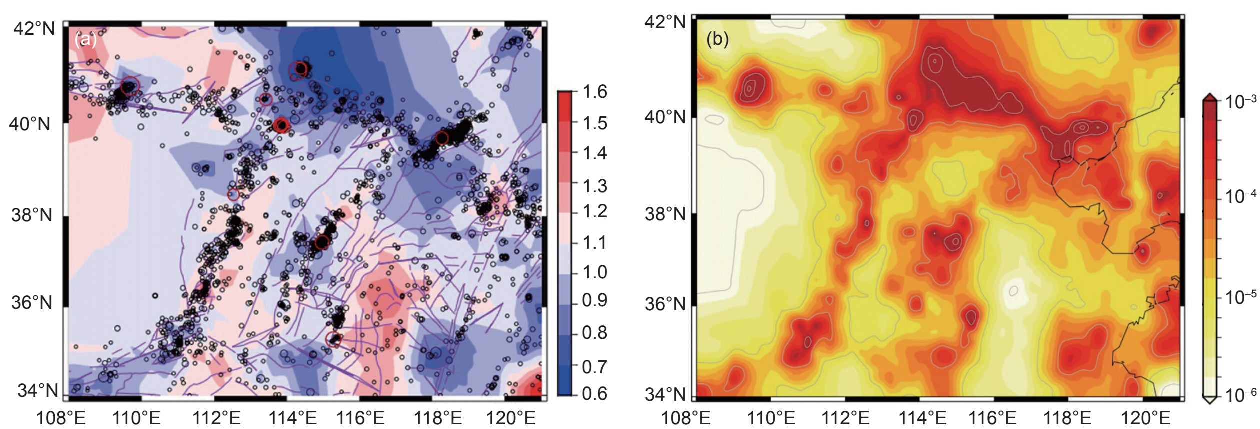

Figure 3 Spatial distribution of *b*-values and the strong seismic hazard prediction map above *M*6 in the study area. (a) Spatial distribution of *b*-values in North China. The black dot indicates the epicenter of earthquakes from January 1, 1980 to December 31, 2016, and the red circle indicates the epicenter of earthquakes of magnitude 5.5 or above. Circles from small to large indicate the magnitudes of earthquakes ranging from 3.0 to 6.2; (b) strong seismic hazard prediction map of earthquakes exceeding *M*6 in the study area (unit: events year^{-1} degree^{-2}) based on the *b*-value distribution map and the earthquake hazard prediction map of earthquakes exceeding *M*3 through their extrapolation of the G-R relationship.

Poisson model described in eq. (1) is applied in the calculation of SHA (Cornell, 1968) and CSHA (Gao, 2015) in the time domain. However, the process of earthquake occurrence exhibited by the stationary Poisson model differs from the physical thought of elastic rebound (Reid, 1910), the classic theory of earthquakes generation. Therefore, many researchers began to find the time-dependent earthquake hazard prediction model. Among these models the SRM proposed by Vere-Jones (1978) is the most representative.

Vere-Jones (1978) suggested the use of conditional intensity to determine the random point process theory that describes the process of earthquake occurrence. Based on the elastic rebound theory, using the random point process theory in statistics, a time-dependent earthquake hazard prediction model, the SRM is proposed. The basic idea is to assume that the occurrence rate of earthquakes in a certain area is related to the area's stress level. The stress level in a given area gradually builds up due to tectonic movement loads, and suddenly decreases, thus coinciding with earthquakes. Therefore, the calculation of the probability of future earthquake occurrence in a given area should be based on the nonstationary Poisson model, and the mathematical expressions are as listed in eqs. (6) and (7) above. To address the limitation of SRM being only suitable for single-fault seismic hazard estimation, Liu et al. (1999a) proposed CSRM, and Jiang et al. (2011) proposed MSRM. MSRM has greatly improved SRM, making it a temporal and spatial seismic hazard statistical prediction model. The Akaike information criterion (AIC) statistical test shows that MSRM not only predicts the more consistent seismic hazard prediction of the entire study area in time (Figure 4a) with observations than SRM or CSRM. More importantly, MSRM can show the spatial distribution of seismic hazard prediction in the study area as shown in Figure 4.

3.4 Probabilistic seismic hazard assessment based on ETAS model

Another important development in the time-dependent earthquake hazard prediction model is the introduction of the idea of branching processes into the Omori-Utsu formula described by Ogata (1988) in eq. (4). It is assumed that each event, regardless of its size, can in principle trigger its own offspring. This new model is called the ETAS, and its mathematical description is as expressed in eq. (8). The ETAS model has been extensively studied and applied since it was proposed. In particular, the rate- and state-dependent friction law have been incorporated into the ETAS model to explain different phenomena in microseismicity (Stein, 1999; Dieterich et al., 2000; Jia et al., 2018), thus significantly improving the influence and application of the ETAS model. Considering the spatial inhomogeneity of seismicity, Ogata et al. further proposed a spatiotemporal ETAS model (Zhuang et al., 2002; Zhuang, 2011). The mathematical expression of the conditional intensity function of the spatiotemporal ETAS model is expressed as follows:

$$\lambda\left(t,x,y \mid H_t\right) = \mu(x,y) + \sum_{i:t_i<t} \xi(t,x,y;t_i,x_i,y_i,m_i). \tag{10}$$

In the above formula, H_t represents the influence of all historical seismic activities on the earthquake occurrence rate at the observation point (x, y) at time t in the study area before time t; $\mu(x, y)$ represents the background earthquake occurrence rate; $\xi(t, x, y; t_i, x_i, y_i, m_i)$ represents the contribution of the ith earthquake to the subsequent seismicity, and its form is expressed as follows:

$$\xi(t,x,y;t_i,x_i,y_i,m_i) = \kappa(m_i)g(t-t_i)f(x-x_i,y-y_i;m_i). \tag{11}$$

Among them, $\kappa(m)$ represents the number of aftershocks expected to be triggered by the main shock with magnitude m, $g(t)$ is the normalized time probability density function, and $f(x, y; m)$ is the spatial probability density function. The specific form is expressed as follows (Zhuang and Ogata, 2006):

$$\kappa(m) = A\mathrm{e}^{\alpha(m-m_c)},\ m \geq m_c, \tag{12}$$

$$g(t) = \frac{p-1}{c}\left(1+\frac{t}{c}\right)^{-p},\ t > 0, \tag{13}$$

$$f(x,y;m) = \frac{q-1}{\pi D^2 \mathrm{e}^{\gamma(m-m_c)}}\left[1+\frac{x^2+y^2}{D^2\mathrm{e}^{\gamma(m-m_c)}}\right]^{-q}, \tag{14}$$

where parameter A (unit: number of events) represents the expected number of earthquakes that can be triggered by an earthquake with an initial magnitude of m_c; α indicates the difference in the triggering abilities of earthquakes of different magnitudes. The difference increases as α increases, which indicates that additional triggers directly contribute to large earthquakes; the p parameter represents the decay rate of aftershocks in time; c (time unit) is inversely proportional to the occurrence rate of child earthquakes when the parent occurs; D (length unit) is the spatial distribution range of earthquakes triggered by an earthquake of initial magnitude m_c, and is inversely proportional to the square root of the occurrence rate of child earthquakes at the location of the

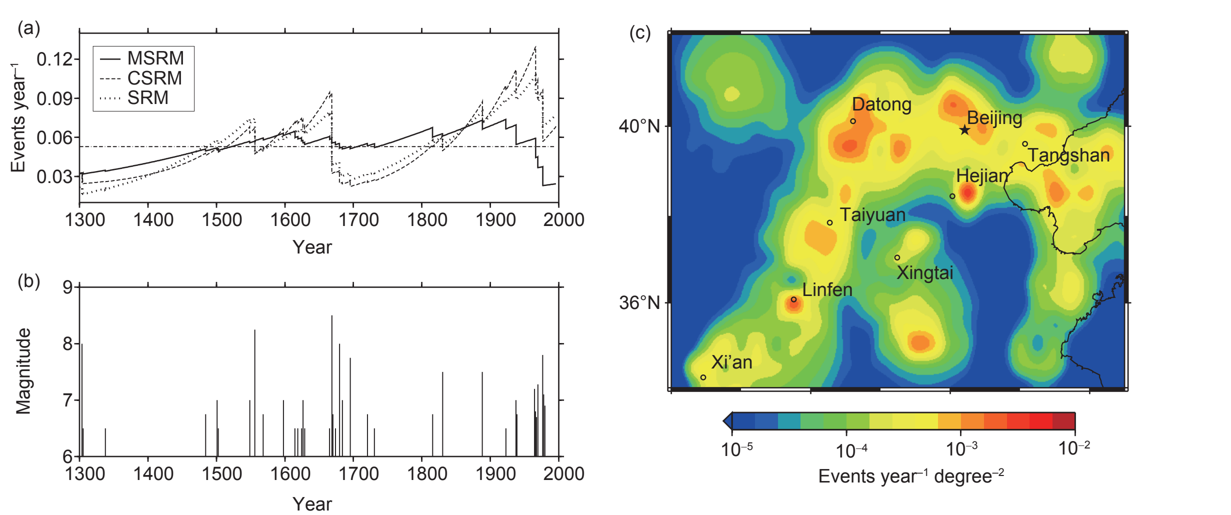

Figure 4 Comparison between strong earthquake hazard with a magnitude of >6 based on SRM, CSRM, and MSRM and the spatial distribution map of a strong earthquake hazard with a magnitude of ≥6 in North China in 2000. (a) The strong earthquake hazard of magnitude ≥6 in the study area obtained by SRM, CSRM, and MSRM based on the catalogue of strong earthquakes of magnitude ≥6 from 1300 to 2000 in North China; (b) *M-t* map of strong earthquakes of magnitude ≥6 from 1300 to 2000 in North China; (c) the spatial distribution map of strong earthquake hazard of magnitude 6 and above in North China in 2000 (modified from Jiang et al. (2011)).

parent; γ is the scaling factor for the spatial distribution of child earthquakes, representing the difference among the spatial distribution of child earthquakes triggered by parent earthquakes of different magnitudes; q represents how fast the aftershock occurrence rate decays in space.

In the calculation, to improve convergence speed, let $\mu(x, y)=\nu u(x, y)$, so there are 8 parameters $\theta=(\upsilon, A, \alpha, c, p, D, q, \gamma)$ that require estimation according to the above formula. The algorithm for solving $\mu(x, y)$ and model parameters $\theta=(\upsilon, A, \alpha, c, p, D, q, \gamma)$ according to the earthquake catalog is reported by Zhuang et al. (2002). The background seismic rate distribution diagrams obtained by different models are shown in Figure 5. Declustering is not required when using the ETAS model to calculate background seismicity, but each earthquake should be weighted based on the estimated results of the model.

4. Consequent challenges in probabilistic seismic hazard assessment and solutions

In the above several statistical seismological methods, strong earthquake hazard prediction is basically based on the extrapolation of the G-R law modeled by a small amount of seismic data. The discrepancy in high magnitude range to fit the G-R law may cause deviations in the results. A few methods such as the SRM (Vere-Jones, 1978), CSRM (Liu et al., 1999a), and MSRM (Jiang et al., 2011), are modeled using historical strong earthquake records to obtain strong earthquake hazard prediction. However, historical data is limited by having a few samples, omissions, and large errors in source parameters. To address these problems, seismologists attempted to establish physical models to carry out seismic hazard prediction through seismicity simulation (Rundle, 1988; Robinson and Benites, 1996; Peresan et al., 2007; Zhou, 2008; Robinson et al., 2011; Jin et al., 2017; Sun and Luo, 2018; Shi et al., 2018).

The second challenge is probabilistic seismic hazard assessment through physical simulation. Through a physical model with reasonable structure, we could simulate the theoretical seismicity in the study area to identify spatio-temporal evolution characteristics of strong earthquake activity and predict regional seismic hazard under the current tectonic background (Ben-Zion, 1996; Ward, 2000; Zhou et al., 2006; Rhoades et al., 2011; Jin et al., 2017). However, the ability of theoretical seismicity to accurately describe the actual situation of seismicity depends on the precision of the source numerical model and the closeness of the simulation

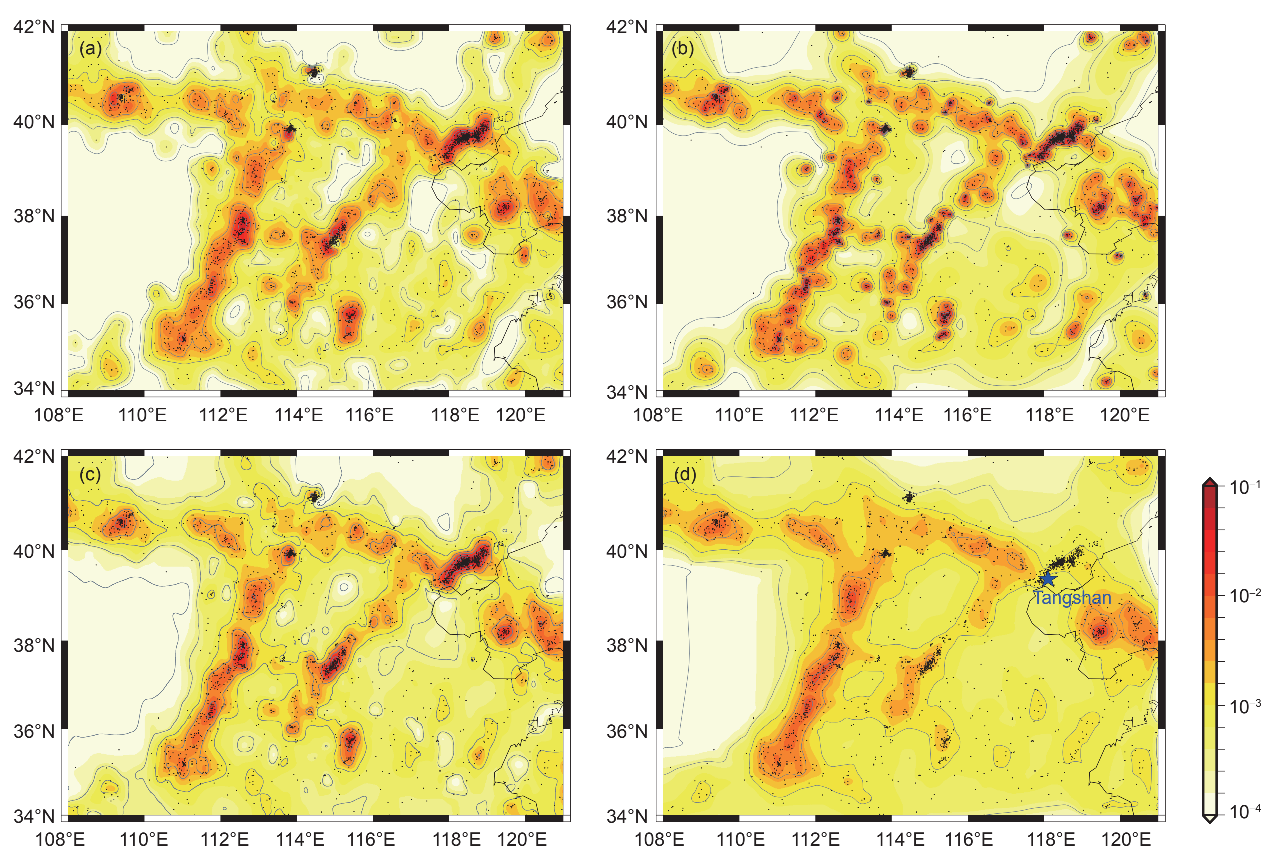

Figure 5 Background seismic rates distribution in North China above magnitude 3 (unit: events year^{-1} degree^{-2}). The results calculated by (a) the S&SK model (Stock and Smith, 2002), (b) the ZOVK model (Zhuang et al., 2002), (C) the ICVT model (Xiong et al., 2019), and (d) Ogata's HIST-ETAS model (Ogata, 2004). This image was obtained from the study conducted by Xiong et al. (2019).

model to the real physical process, for use in seismic engineering research and seismic hazard prediction (Ma and Wu, 2013; Shi et al., 2013). In recent years, many research results on large earthquake rupture process and source dynamics offered a lot of relevant insight into the seismogenic mechanism, hindering the generation of a simulation model to obtain theory seismic activities, which reflects real tectonic activity and seismic activity. At the same time, the accumulation of observation data from many seismic and GPS arrays is conducive to obtaining a more refined structure model of the study area. Shi et al. (2013) summarized the five key requirements for the numerical prediction of earthquakes: (1) A clear understanding of the seismogenic process and ability to quantitatively express this strictly using mathematical and physics equations; (2) The ability to solve these equations; (3) The model based on monitoring the regional structure, physical properties and states in detail, for a specific forecast; (4) Boundary conditions and their changes over time; (5) Initial conditions of dynamic equations. The first two parts will gradually be resolved with the development of computing technology and seismology, and the latter three parts can only rely on very dense geophysical observations (mainly earthquake and deformation observations). However, even in Parkfield, California, where the geophysical observations are most dense, the resolution and accuracy of the regional underground structures obtained now are far from the requirements of digital earthquake prediction based on physical models. Academician Shi Yaolin reported difficulties in addressing the five aforementioned factors to realize numerical earthquake prediction. However, long-term probabilistic seismic hazard prediction based on existing seismological theories and simple regional structure model supported by modern observations is possible. (Shi et al., 2018) Furthermore, the scale of decades or a hundred years is the concern of earthquake engineering, which is the most promising to introduce numerical simulation to carry out probabilistic seismic hazard prediction based on physical models, to solve the aforementioned difficulties, particularly, to prevent the deviation caused by the extrapolation of G-R law.

Because a more detailed structural model of the study area is required to build physical model. Despite being based on the resolution of the existing observations and imaging results of crustal structure, only a few areas can meet the basic requirements of the compilation of seismic zoning map of ground motion. Therefore, the application of potential seismic source zones is a practical and scientific choice for CSHA in the compilation of seismic zoning map of ground motion in the Chinese mainland (Gao, 2015). However, since the determination of potential seismic source area requires many geological surveys and great experience, detecting active faults and determining potential seismic source areas where large urban agglomerations are mostly built with thick deposits and low seismicity are difficult.

In recent years, according to modern earthquake catalogues, using ETAS models to build probabilistic seismic hazard prediction models has begun to garner attention and applications in the field of earthquake engineering in Japan, the United States, Italy, and other countries (Zhuang, 2011; Ogata, 2011; Werner et al., 2011; Taroni et al., 2018; Schorlemmer et al., 2018; Fields, 2019). The Working Group on California Earthquake Probabilities, the National Institute of Geophysics and Volcanology, and the GEM project have all began to accept the idea of statistical seismology and a time-dependent model such as ETAS, which was developed from statistical seismology, as the basis and tool of probabilistic seismic hazard prediction for testing hypotheses (Huang et al., 2016). The seismic hazard prediction based on modern earthquake catalogues is also limited by its need to extrapolate the seismic hazard of high magnitude according to the G-R law. According to the latest results of the research on rupture dynamics of the academician Chen Xiaofei's research group (Xu et al., 2015; Zhang et al., 2017a), the upper boundary extrapolated by the G-R law maybe 6.0–6.5, which means that the seismic hazard prediction map based on catalogues is extrapolated to magnitude 6 with greater reliability. Therefore, the seismic hazard assessment based on modern earthquake catalogues in most regions should be effective. Particularly, the application of seismic hazard assessment based on ETAS should be the easiest and most effective in the compilation of seismic hazard maps in large urban agglomeration areas and low seismic hazard areas with thick sedimentary areas.

Acknowledgements *The catalogs used in this article were obtained from the China Earthquake Network Center (http://www.ceic.ac.cn/history). We appreciate Mengtan GAO for helping us clarify the main issues concerning the national seismic zoning maps of China. This work was supported by the National Natural Science Foundation of China (Grant No. U2039204) and the National Key R&D Program of China (Grant No. 2018YFC1504203).*

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(Responsible editor: Ling CHEN)