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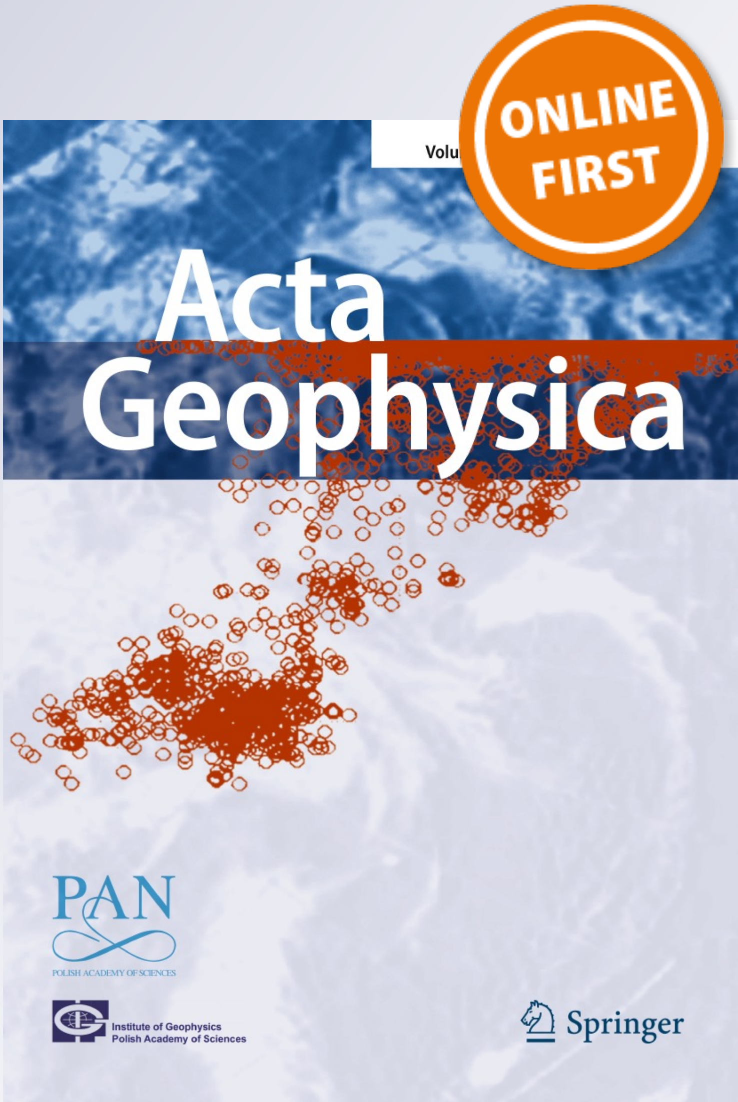

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Modeling the earthquake occurrence with time-dependent processes: a brief review

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Abstract

The complexity of seismogenesis tantalizes the scientific community for understanding the earthquake process and its underlying mechanisms and consequently, precise earthquake forecasting, although a realistic target, is yet far from being a practice. Therefore, seismic hazard assessment studies are focused on estimating the probabilities of earthquake occurrence. For a more precise representation of seismicity-regarding time, space and magnitude stochastic modeling is engaged. The candidate models deal with either a single fault or fault segment, or a broader area, leading to fault-based or seismicity-based models, respectively. One important factor in stochastic model development is the time scale, depending upon the target earthquakes. In the case of strong earthquakes, the interevent times between successive events are relatively large, whereas, if we are interested in triggering and the probability of an event to occur in a small time increment then a family of short-term models is available. The basic time-dependent models that can be applied toward earthquake forecasting are briefly described in this review paper.

Keywords Time-dependent seismicity models · Stochastic · Long- and short-term · Earthquakes forecasting

Introduction

Estimating the occurrence time of future earthquakes, in a given area, is an indispensable component in seismic hazard assessment studies. It can be made possible through the analysis of the temporal seismicity properties, and consequently the development of models that can imitate the earthquakes temporal behavior. The application of stochastic rather than deterministic models is affected by the limited number of the available data (instrumental records and historical seismic catalogs) as well as the fact that seismogenesis is a self-organized system, related with many complex phenomena (e.g., fault heterogeneity). While a deterministic model aims at fully describing the phenomenon and making exact predictions, a stochastic model introduces a certain level of randomness into the physical process under study, resulting in a forecast of future events. Regarding this distinction, earthquake forecasts based on stochastic models are given in terms of occurrence probabilities. Stochastic models may be based on the memoryless Poisson process or on other processes containing memory, such as short- and long-term cluster behavior (Kagan and Jackson 1991) or quasi-periodic occurrence (Papazachos et al. 1997a). Given that earthquakes are clustered in time, some kind of memory is implied and thus, the most appropriate models are the time-dependent ones.

Two different main approaches prevail when developing and applying time-dependent stochastic models. In the "fault based" approximation the studies deal with the interevent times between successive strong earthquakes occurring on an individual fault or fault segment above a certain magnitude threshold. The target of these models is the estimation of the long-term recurrence of strong events in a given area where faults are well known. As already mentioned, earthquake occurrence is a complex physical process including

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fault heterogeneity and interaction between nearby faults leading to a collective behavior, which can potentially cause triggering of adjacent fault segments in short-term time scales. These physical processes can be modeled through the second family of stochastic approaches, the so-called seismicity based ones, which assume that the future earthquakes are characterized by the temporal properties of the past events within a specific region due to all possible seismic sources, not only the large and well known but also the smaller ones (Frankel 1995).

Fault-based models

The construction of a fault-based model

The available data (geological and geodetic) along with the longest possible record of past ruptures (historical and instrumental) of the fault segments under study are required for the development of a fault-based model. Using this information, the model can then be built with the combination of the assumptions of the time-predictable model (Shimazaki and Nakata 1980) and the characteristic earthquake hypothesis (Schwartz and Coppersmith 1984). The time-predictable model assumes that the occurrence of an earthquake is observed when stress surpasses a given constant threshold. Thus, the estimation of the next event is achieved considering the coseismic slip of the previous earthquake (Fig. 1). According to the characteristic earthquake hypothesis, strong earthquakes on a fault occur regularly and they are characterized by similar physical mechanisms. Thus, a future strong earthquake occurs as the result of the long-term tectonic loading on a given segment.

Consequently, the final output of such a model will be single or multi-segment long-term Earthquake Rupture Forecasts (ERF) in a specific time window. The distribution of the recurrence time of strong earthquakes constrained with the occurrence time of the last strong earthquake on a certain fault segment is given by the formula:

$$P(T \leq t \leq T + \Delta T | t > T) = \frac{\int_T^{T+\Delta T} f(t)\mathrm{d}t}{\int_T^{\infty} f(t)\mathrm{d}t}$$

where t stands for the time relative to the previous earthquake under the condition that T years passed since the last event, ΔT stands for the duration of the forecast and $f(t)$ stands for the probability density function of the recurrence time (Field 2015).

The problem of the distribution fitting

The major task for these renewal models is the selection of the appropriate distribution that the recurrence time follows. Among the most common distributions used for this purpose, the Weibull, the Lognormal and the Brownian passage time (BPT) distributions dominate (Convertito and Faenza 2014). The Weibull distribution probability density function (pdf) is given by

$$f(t|a, b) = \frac{b}{a}\left(\frac{t}{a}\right)^{(b-1)} \exp\left\{-\left(\frac{t}{a}\right)^{b}\right\}$$

where α and b stand for the scale and the shape parameter, respectively. An interesting feature of this distribution, which is connected with the seismicity, is the value of the shape parameter, b. If the parameter b is equal to 1 ($b = 1$) then the distribution is reduced into the exponential one. If b is less than 1 ($b < 1$), then the model can be considered as a short-term clustering one, while if b is greater than 1 ($b > 1$), then the model can be characterized as quasi-periodic, which is the case in the fault-based models.

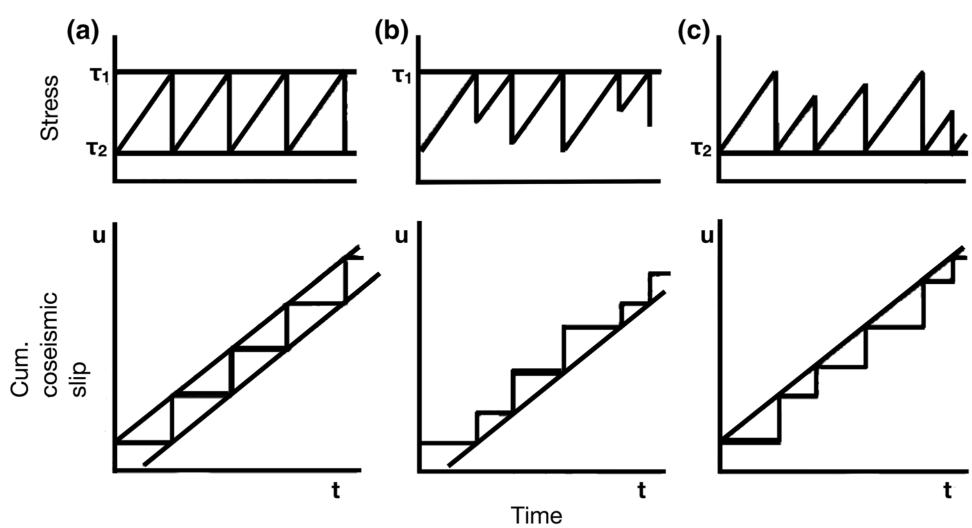

Fig. 1 Representation of the evolution of stress (upper panel) and corresponding slip (lower panel) with time on a certain fault, considering characteristic (**a**), time-predictable (**b**) and slip-predictable (**c**) earthquake occurrence models. (modified from Shimazaki and Nakata 1980)

The lognormal distribution pdf is formulated by the equation

$$f(t|\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma t}\exp\left\{-\frac{(lnt-\mu)^2}{2\sigma^2}\right\}$$

where μ is the mean and σ is the standard deviation of the natural logarithm of the data sample, such as the recurrence intervals between strong earthquakes. Lognormal distribution is one of the so-called heavy tail distributions, which return high values of probability for variables that have larger return periods than the average one.

Kagan and Knopoff (1987) tried to describe the earthquake occurrence by modeling the evolution of stress as a random walk, or in other words as a Brownian motion, incorporating the inverse Gaussian distribution. The pdf of the inverse Gaussian distribution is given by

$$f(t|\mu,\lambda) = \sqrt{\frac{\mu}{2\pi t^3}}\exp\left\{\frac{-\lambda(t-\mu)^2}{2\mu^2 t}\right\}$$

where μ and λ are the mean value of the data sample and the shape parameter. Ellsworth et al. (1999) and later Matthews et al. (2002) extended the aforementioned idea and proposed a renewal model based on an experimental one introducing the Brownian Relaxation Oscillator (BRO). This model assumes that the earthquake occurrence is driven by the equation

$$X(t) = \lambda t + \sigma W(t)$$

where $X(t)$ is the stress level, λ is the constant loading rate and $\sigma W(t)$ is a random factor following the properties of the Brownian motion in which σ is a nonnegative scale parameter and *W(t)* is the standard Brownian motion. The resulting recurrence properties of the model (the recurrences of strong earthquakes) are described by the Brownian passage time (BPT) distribution, which is an alternative form of the inverse Gaussian one given from the relation

$$f(t|\mu,\alpha) = \sqrt{\frac{\mu}{2\pi\alpha^2 t^3}}\exp\left\{\frac{-(t-\mu)^2}{2\mu\alpha^2 t}\right\}$$

where μ is the mean value of the data sample and α is the model's aperiodicity, which must take values greater than 0 ($0 < \alpha < \infty$). Aperiodicity can be considered as the analogous of the coefficient of variation of the Gaussian distribution, and it represents the model level of randomness. As α tends to 0, the model becomes increasingly periodic. As α tends to ∞ the model becomes increasingly aperiodic. All the intermediate cases represent quasi-periodic models with a certain level of randomness. In most strong earthquakes recurrence studies, the value of a ranges between 0.3 and 0.7 ($0.3 \le a \le 0.7$) (e.g., Field et al. 2015).

Zoller et al. (2008) introduced an alternative expression of the BPT distribution, where the contribution of small and intermediate earthquakes on the state changes before strong earthquake occurrence is taken into account. Following this approach, we assume that the on-fault seismicity provokes delay of the next large events by unloading the fault, while the off-fault seismicity loads the fault. If these effects are considered approximately equivalent, then the aperiodicity is related to the b-value of the instrumental catalog of the corresponding fault according to the following relation

$$\alpha = \sqrt{\frac{b}{3-b}}$$

where b must be ranging between $0<b<3$. Then, the BPT pdf can be written as

$$f(t|\mu,b) = \sqrt{\frac{\mu(3-b)}{2\pi t^3 b}}\exp\left\{\frac{-(t-\mu)^2(3-b)}{2tb\mu}\right\}$$

BPT model has become the most popular one over the years in studies dealing with the recurrence times of strong earthquakes. This is due to the fact that the temporal behavior of strong earthquakes is fairly explained through its hazard function (Fig. 2). The values of the hazard function, i.e., the hazard rate, which is equivalent to the conditional probability, are very low immediately after the occurrence of an event and then they exhibit an increasing trend with time. The maximum value is obtained at some finite time near the mean recurrence time. Then, the hazard rate decreases asymptotically to $1/(2\mu\alpha^2)$. In contrast, the Weibull hazard function increases monotonically with time after a strong event (e.g., the blue line of Fig. 2 right panel) and the lognormal hazard function increases to a maximum and then decreases asymptotically to zero.

An alternative distribution has been proposed by Polidoro et al. (2013), the Erlang distribution, which is a Gamma distribution with pdf

$$f(t|k,\lambda) = \frac{\lambda(\lambda t)^{k-1}}{\Gamma(k)}\exp\{-\lambda t\},$$

where k is the shape parameter, λ is the scale parameter and Γ is the gamma function. Regarding the probabilistic seismic hazard analysis, the aforementioned distribution suggests that in a small time interval the occurrence of more than one earthquake is unlikely. The inverse Gamma distribution is also proposed by Polidoro et al. (2013), assuming that the load on the fault increases linearly over time, with a rate that varies randomly from event to event. The pdf is given by the following relation

$$f(t|\gamma,\beta) = \frac{\beta^\gamma}{\Gamma(\gamma)}\left(\frac{1}{t}\right)^{\gamma+1}\exp\left\{-\frac{\beta}{t}\right\},$$

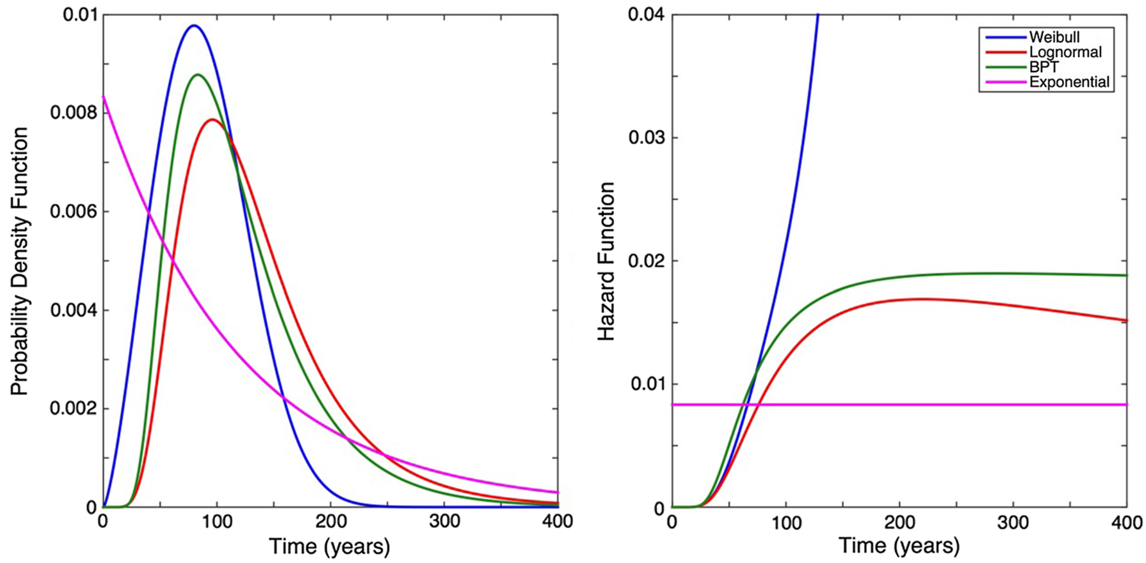

Fig. 2 Example of probability density functions (left) and their corresponding hazard functions (right) of the main renewal models (Weibull, Lognormal and BPT) against the memoryless one

where γ and β the shape and scale parameters, respectively. Over the years, recurrence models were refined more and more, aiming at improving their predictive power and increasing the accuracy of their estimations for seismic hazard, incorporating processes like the permanent and temporal stress perturbations in combination with a particular pdf of recurrence time (Stein et al. 1997; Hardebeck 2004; Gomberg et al. 2005).

Applications

One of the first relevant applications was performed by Hagiwara (1974), who used the Weibull distribution assuming that the crust is strained under a constant speed. Earthquakes with $M \geq 6.0$ along South Kanto District in Japan were considered and it was found that the maximum value of the conditional probability of a future event is expected in 84 years after the last earthquake. Rikitake (1974, 1976) used the same distribution to estimate the probabilities of strong future events ($M \geq 8.0$) along the subduction zones of Japan, Kurile, Aleutian Islands, Kamchatka, and Americas (North, Central and South) considering that the ultimate crustal stain increases linearly with time and that immediately after a strong event is nearly zero. He evidenced the long-term time dependence (e.g., for the Kanto area in Japan, where the last strong event occurred in 1925 with $M = 7.9$ the probability values were found equal to 0.2, 0.5 and 0.8 for the next 55, 105 and 155 years, respectively). More recently, Abaimov et al. (2008) also applied the Weibull distribution on characteristic events of Parkfield and Wrightwood fault segments of San Andreas fault zone. Their best fitting models resulted in quite similar mean and standard deviation values to the observed ones, suggesting Weibull as the most suitable distribution for such studies.

Nishenko and Bulland (1987), attempting a time-dependent probabilistic approach to describe earthquake occurrence and its corresponding seismic hazard, proposed a generic recurrence time model adopting the Lognormal distribution. They concluded that the Lognormal distribution exhibits a significant better fit than the Weibull using recurrence times of earthquakes with *Mo* between 10^{17} and 10^{23} Nm, occurred in the major fault segments of Mexico, Chile, California, Japan and Alaska through a normalized function. Following their suggestion, Jackson et al. (1995) summarized the results of the Working Group on California Earthquake Probabilities (WGCEP), adopting the Lognormal as the optimal statistical model. Their model estimates a probability equal to 80%–90% for an $M \geq 7.0$ expected earthquake in California before 2024. The Lognormal distribution was also used by Paradisopoulou et al. (2010) in fault segments across Western Turkey, incorporating the static stress changes into the probability estimates.

Ogata (2002) used the BPT distribution constructing a slip-size dependent renewal model, incorporating the knowledge of the slip associated with strong earthquake ruptures. The application of the model was performed on the large historical earthquakes along Nankai Trough ($M \approx 8.0$) and Off Toyooka fault ($6.0 \leq M \leq 7.0$) in Japan. He found that the single BPT model for the Nankai Trough returned a likely occurrence time around 2070, but with large uncertainty (> 100 years). When the slip-size dependent model was used considering the last three events of this catalog, then the estimated hazard function assumes that the next earthquake's occurrence is expected around 2040. The model was also used for the second data set exhibiting that the next occurrence time in this case is decreasing. Parsons (2004) applied the BPT model for the estimation of $M \geq 7.0$ earthquakes occurrence probabilities on single fault segments beneath the Sea of Marmara, after taking into account the coseismic and postseismic stress transfer in the calculations. The same author (Parsons 2008) modeled the recurrence times of characteristic earthquakes on Hayward fault segment in California with the use of the BPT model and concluded in the superiority of this renewal model in respect to the memoryless one. Console et al. (2008) studied the effect of such stress interactions between nearby faults of Central and South Apennines region in Italy also using the BPT model, concluding that this effect was relatively small. Parsons et al. (2012) and Murru et al. (2016) took into account the effect of static stress transfer from previous earthquakes to the next ones in Nankai Trough in Japan and Sea of Marmara in Turkey fault systems, respectively, using the BPT distribution on their recurrence modeling.

Focusing on similar applications in Greece, Console et al. (2013) applied two renewal models, the BPT and the Weibull, against the memoryless Poisson one, in each one of the eight fault segments consisting the Corinth Gulf fault system, after taking into account the effect of stress transfer in their calculations of conditional occurrence probability values (Fig. 3). The North Aegean Trough (NAT) fault system was also studied under the BPT renewal model, considering a new segmentation model and two different assumptions of strong earthquakes magnitude completeness (Kourouklas et al. 2018).

Polidoro et al. (2013) applied many different distributions, among them the BPT, the inverse Gaussian and the Erlang distribution, in the Paganica fault (Central Italy). They found that when the time elapsed since the last earthquake is about half of the return period of the event, then all models exhibit similar results. This means that the longer is the time since the last event, the more critical is selecting the appropriate model. For example, a decreasing occurrence probability implied by some distributions is not representative of seismogenesis.

Special mention must be paid to the Uniform California Earthquake Rupture Forecast (UCERF) versions 2 (Field et al. 2009) and 3 (Field et al. 2015), which are the best developed models for long-term time-dependent probability estimations. These approaches combine a large variety of seismological, geological and geodetic information constructing different fault, deformation and earthquake rate models for each fault segment of California, which form a logic tree with a large number of branches (e.g., version 3 has a total number of 5760) with their corresponding weights. Then the probability calculations were based on the aforementioned assumptions having as final product different estimations of the next earthquakes in California, with their corresponding weights and uncertainties. The renewal model used in these estimations is the BPT once again.

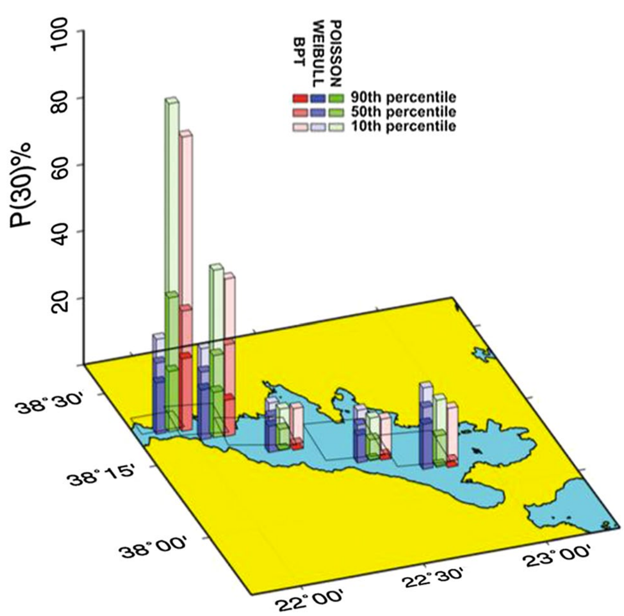

Fig. 3 Thirty years conditional occurrence probabilities along Corinth Gulf fault system according to Poisson, BPT and Weibull models. (From Console et al. 2013)

Seismicity-based models

Assumptions and forecast windows

"Seismicity based" models belong to the second category of stochastic models assuming that the future earthquakes follow the temporal properties of the past seismicity within a given region due to all possible seismic sources. These models combine both physical processes related to strong earthquakes occurrence, such as the accumulation, release and transfer of stress, and the well-known empirical laws of Seismology, namely the Gutenberg–Richter (GR) (Gutenberg and Richter 1949) and the Omori's (Omori 1894). Model applications can provide either long-term or short-term estimations of next earthquakes in a given region.

Long-term regional models

Starting with the long-term ones, Papazachos (1989) suggested a time-predictable model for earthquake occurrence in seven distinctive regions of Greece, using all available

$M \geq 5.5$ earthquakes located in the area. He claimed that the magnitude of the preceding shock, Mp, influences the repeat time, T, of the next mainshocks. The model he developed is based on the linear fit between the logarithm of T and Mp:

$$logT = cMp + a.$$

Papadimitriou (1993) applied the aforementioned model in 8 zones of the western coast of South and Central America. Papazachos (1992) and Papazachos and Papaioannou (1993) extended the time-predictable model to the time and magnitude one. They are given by two relations: one between the logarithm of T and the minimum magnitude considered in the dataset,$Mmin$, the magnitude of the previous shock, M_p, and the logarithm of the annual moment rate, m_o, and a second relation linking the magnitude of the following mainshock, M_f, and the above mentioned parameters as,

$$logT = bMmin + cMp + dlogm0 + q$$

and

$$Mf = BMmin + CMp + Dlogm0 + m.$$

This extended model was used in several studies all over the world. For example, Karakaisis (1993, 1994a, b) applied the models in New Guinea–Bismarck Sea, North and East Anatolian Fault Zones and Iran regions. Panagiotopoulos (Panagiotopoulos 1994, 1995) applied the time- and magnitude-predictable models in Solomon Islands, Central America and Caribbean Sea, Papadimitriou (Papadimitriou 1994a, 1994b) in North Pacific and Tonga–New Zealand seismic zones, Papazachos et al. (1994, 1997a, b) in Japan, circum–Pacific and Alpine–Himalayan belts and a few years later Shanker and Papadimitriou (2004) in the Hindu Kush–Pamir–Himalayan region. Similar to these studies Musson et al. (2002) proposed a similar time-dependent model connecting the natural logarithm of interarrival times, $lnIAT$, with their magnitudes, M, above a given threshold:

$$lnIAT = a + bM$$

and applied it in Japan and Greece. Later, Chingtham et al. (2015) applied this model in Northwest Himalaya and its adjoining regions.

A connection between seismicity and physics is accomplished through the Stress Release Model (Vere-Jones 1978; Vere-Jones and Deng 1988) which is built under the assumptions of stress loading due to elastic rebound and energy released when an event occurs (Fig. 4). The main variable is the stress level which can be written as

$$X(t) = X(0) + \rho t - S(t),$$

where $X(0)$ is the initial stress level, ρ is the loading rate (which is considered constant) and $S(t)$ is the accumulated stress release during $(0, t)$. The conditional intensity function

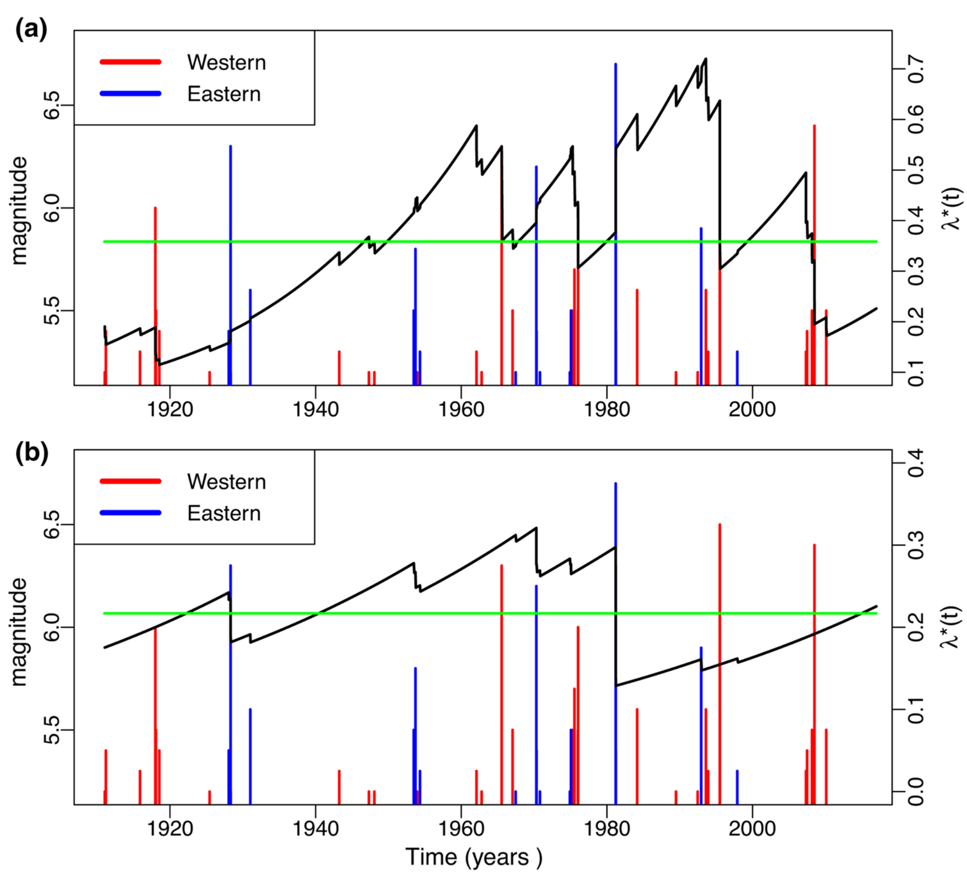

Fig. 4 Plots of the conditional intensity functions when the LSRM is applied in the Corinth Gulf (Greece) **a** Western part, **b** Eastern part. The mean occurrence level of the Poisson model is represented by a green line (From Mangira et al. 2018)

$\lambda * (t)$, (Daley and Vere-Jones 2003) determines the stochastic behavior of the point process. The most common form adopted is the exponential

$$\lambda * (t) = \Psi(X(t)) = \exp\{a + b[t - cS(t)]\}$$

where a, b and c are parameters to be estimated.

In the case of the Linked Stress Release Model (Liu et al. 1998), the conditional intensity function becomes

$$\lambda_i^*(t) = \exp\left\{ a_i + b_i \left[t - \sum_j c_{ij} S(t,j) \right] \right\}.$$

In this model, stress transfer and interactions between subareas are introduced. Many applications of the model have been performed worldwide. The first applications include Chinese (Liu et al. 1999), and Japanese data (Lu et al. 1999). Lu and Vere-Jones (2000) compared the results applying the model in two different tectonic regimes (North China and New Zealand), whereas Bebbington and Harte (2001) examined the model from a statistical point of view. SRM was also applied in Italy, where Varini and Rotondi (2015) and Varini et al. (2016) used a Bayesian approach. Romania (Imoto and Hurukawa 2006) and Greece (Rotondi and Varini 2006; Votsi et al. 2011; Mangira et al. 2017, 2018) have also been study areas for the SRM. Bebbington and Harte (2003) conducted an extensive study regarding the determination of the regions, the sensitivity to catalog errors optimization techniques, and the selection of the most appropriate model. Numerical simulations by Kuehn et al. (2008) aimed at investigating how the occurrence probability distributions are affected by the coupling between different areas.

The observed foreshock activity before strong earthquakes in many regions around the world (Jones and Molnar 1979; Sykes and Jaume 1990; Bakun et al. 2005) was also used as a tool aiming at the development of physics-based models for forecasting. A relevant approach, so-called Accelerating Moment Release (AMR) model or critical earthquake concept, was developed under the assumption that before a large earthquake, and the rate of seismic moment released from precursory intermediate magnitude (e.g., $M \geq 5.0$) seismic activity is increased with an accelerating component (Bufe and Varnes 1993; Bowman et al. 1998; Jaume and Sykes 1999; Mignan 2008).

Bufe and Varnes (1993) proposed that the cumulative Benioff strain,$\varepsilon(t)$, over time, which is equal to the summation of the square of the seismic moment of the ith foreshock, Ei, defined as

$$\varepsilon(t) = \sum_{i=1}^{N(t)} \sqrt{E_i}$$

can be expressed by the equation

$$\varepsilon(t) = A - B\left(t_f - t\right)^m$$

where t_f is the time of a mainshock or in other words the critical occurrence time of the upcoming strong earthquake, A and B are constants and m is a positive exponent ranging from 0.1 to 0.5 ($0.1 \leq m \leq 0.5$) with mean value equal to 0.3. The AMR model has been applied in many studies and in various regions worldwide such as California (Bowman et al. 1998), Italy (Di Giovambattista and Tyupkin 2000), China (Jiang and Wu 2006), Western, South and Central America (Papazachos et al. 2008) and Greece (Papazachos et al. 2006, 2007).

Another class of stochastic models includes the hidden Markov (HMMs) and semi-Markov (HSMM) models. The main concept of the HMMs applied in seismology is to reveal features of the earthquake generation process which cannot be directly observed. Toward that direction, Votsi et al. (2013) applied a HMM, where the states of the model correspond to levels of the stress field. Their application is performed in a set of strong ($M \geq 6.5$) earthquakes that occurred in Greece and its surrounding areas, since 1845. In order to overcome the drawback that derives from the geometrically distributed sojourn times of the HMM states and allow arbitrary distributions, the same authors (Votsi et al. 2014) suggested a discrete-time semi-Markov model. Pertsinidou et al. (2016) extended their work proposing Poisson, Logarithmic and Negative Binomial distributions for the sojourn times. Their application is performed in moderate ($M \geq 5.5$) earthquakes in the areas of North and South Aegean Sea (Greece) where the hidden states represent different stress levels classified into five types according to the earthquake magnitude and location.

Different occurrence rates are also considered as hidden states in the case of Markovian Arrival Processes suggested by Bountzis et al. (2018). MAP consists a generalization of the Poisson process and renewal models preserving the Markovian structure. The model captures temporal fluctuations that characterize Corinth Gulf seismicity for earthquakes with $M \geq 4.5$ since 1964.

Short-term modeling of regional earthquake activity

In addition to the long-term earthquake forecasting, extensive research was performed on short time scales. One of the most crucial elements regarding an earthquake time series is their tendency to clustering. It is generally accepted that seismic activity is increased after the occurrence of a strong event for several years (Utsu et al. 1995) and for long distances (Kagan and Jackson 1998; Dreger and Savage 1999). When the magnitude of an event is smaller than that of the previous one, the triggered event is called an aftershock. Defining an aftershock is quite arbitrary though and separating triggering earthquakes from the others is not a trivial task. Since the classification of an earthquake foreshock, mainshock, or aftershock—is often hard, it is useful to investigate models that do not presuppose such distinction. In addition, aftershocks constitute the greatest proportion in a catalog and thus, a thorough analysis of their occurrence can give an insight for understanding the whole seismic cycle. Ogata (1988) introduced a model where there is no need to distinguish between mainshocks and aftershocks, between independent and triggering events, since each one, irrespective of whether it is small or large, can trigger its own offspring. The ETAS (Epidemic-Type Aftershock Sequence) model, named after the analogy with the spread of epidemics, belongs to the family of self-exciting Hawkes processes (Hawkes and Oakes 1974). It is assumed that each event is followed by its own aftershock activity; this assumption stands even for the aftershocks of the previous events. The modified Omori formula (Utsu 1961) is employed for the representation of the aftershock activity. The appropriate form of the response function for the causal relation with subsequent events is the key for the application of the model. The conditional intensity is given by

$$\lambda(t,m) = \beta e^{\beta(m-m_0)}\{\mu + A\sum_{i:t_i<t} e^{a(m-m_0)} f(t-t_i)\},$$

where μ represents the background seismicity,A is related to the criticality of the process, a is related to the productivity, i.e., the influence of magnitude in the production of the offspring and $\beta = bln10$ is linked to the G–R law. $f(t) = (p-1)\left(1+\frac{t}{c}\right)^{-p}/c$ refers to the Omori–Utsu formula and it is the pdf of the time difference between the parent event and its offspring. Based on the temporal model of Ogata (1988) many applications have been performed. For example, Ogata (2005) tried to detect anomalous seismicity patterns using it as a stress change sensor. Hainzl and Ogata (2005) and Lombardi et al. (2010) used the ETAS model for detecting fluid signals. They interpreted the increase in the background seismicity as fluid-driven earthquake triggering.

In a similar manner with the temporal ETAS model, Ogata (1998) deals with the response function for time and space causal relationship introducing the spatiotemporal ETAS model. The concept of this model is to investigate the magnitude scale of the clusters and also to understand whether the clusters are constrained to well-defined areas or if seismic activity is extended in areas beyond the aftershock regions. When space is involved the conditional intensity takes the form

$$\lambda(t,x,m) = \beta e^{\beta(m-m_0)}\{\mu h(x) + A\sum_{i:t_i<t} e^{a(m-m_0)} f(t-t_i) g(x-x_i)\}.$$

The new terms added in the model are the spatial density, h, of the background events and the density, g, of the location of a triggered event. The model proposed by Ogata (1998) underwent several modifications, particularly concerning the spatial component (Zhuang et al. 2002, 2004, 2005; Ogata and Zhuang 2006), and it is broadly accepted and applied.

Based on the assumption that every event is potentially triggered by all the previous ones and every event can trigger subsequent ones according to their relative time–space distance, Console and Murru (2001) proposed a spatiotemporal model for short-term clustering that returns the occurrence rate of events expected at each point of the location–time–magnitude space. They concluded that instead of using as a null hypothesis the Poisson model against other more sophisticated earthquake hypotheses, the clustering hypothesis (the space–time ETAS model) should be adopted since it exhibits a much higher likelihood. Console et al. (2003) refined the formulation of the clustering model. The expected earthquake rate density takes then the form

$$\lambda(x,y,t,m) = f_r\lambda_0(x,y,m) + \sum_{i=1}^{N} H(t-t_i)\lambda_i(x,y,t,m),$$

where the f_r, called failure rate, expresses the proportion of events that are considered independent, a factor revealing the so-called spontaneous background seismicity. The $\lambda_0(x,y,m)$ is the spatial magnitude distribution, $H(t)$ the step function, i.e., $H(t) = \begin{cases} 0, & if\ t \le 0 \\ 1, & if\ t > 0 \end{cases}$ and $\lambda(x,y,t,m)$ is the kernel of the previous events. In this equation, the two terms of the right-hand side show that seismicity is a mixture of the background, the independent events, and the induced ones. The model could provide daily expected seismicity rates, information extremely critical during a seismic excitation. Examples of expected daily seismicity rate forecast provided by the ETAS modelare shown in Fig. 5 (From Murru et al. 2014).

The ETAS model examines earthquake clustering from a purely statistical point of view. Fault interaction consists of a way to connect seismicity and physics. Since it is broadly recognized that sudden Coulomb stress changes due to the coseismic slip of preceding earthquakes can modify the proximity to failure of subsequent events, Console et al. (2006a, b) proposed a modification of the clustering model by including the rate-and-state theory developed by Dieterich (1994) in the concept of the ETAS model. According to this theory, the seismicity rate $R(t)$ of earthquakes when a stress change is observed at time $t = 0$ is written:

$$R(t) = \frac{R_o}{1-\left[1-\exp\left(-\frac{\Delta\tau}{A\sigma}\right)\right]\exp\left(\frac{-t}{t_a}\right)}$$

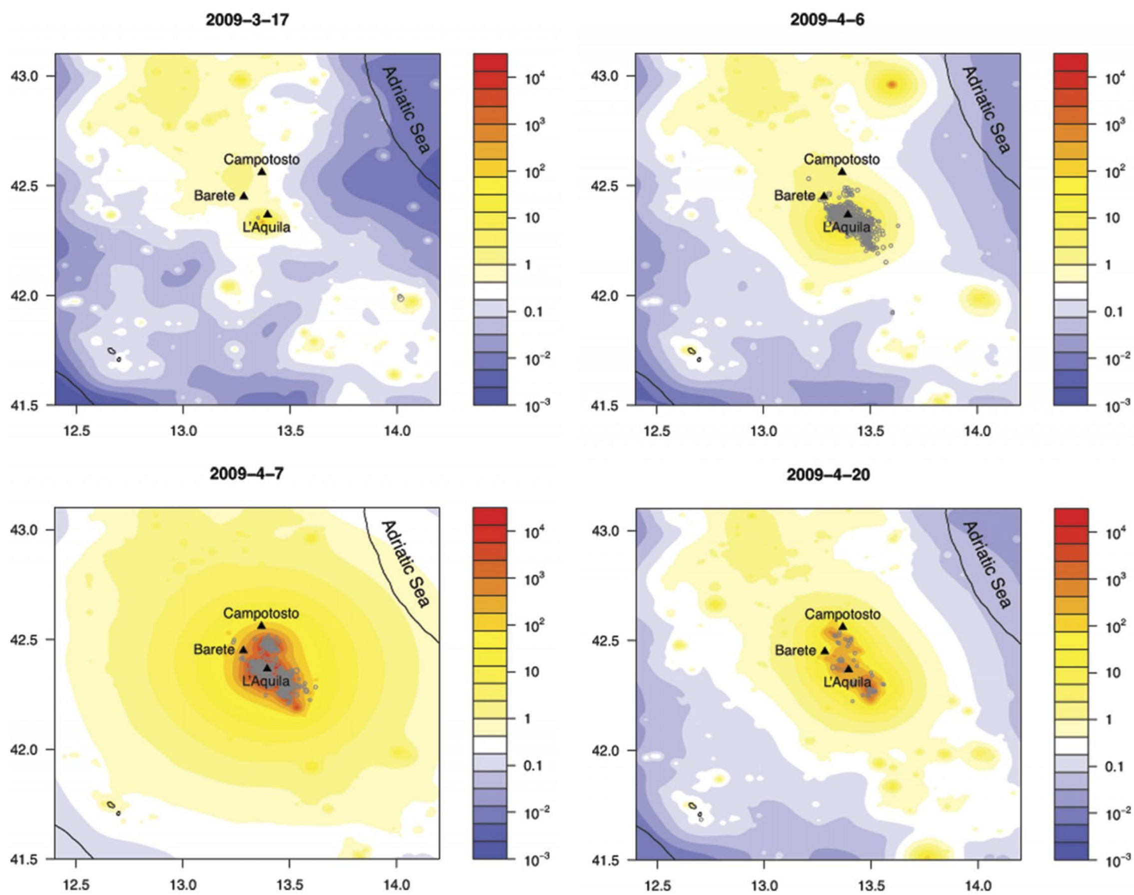

Fig. 5 Examples of expected daily seismicity rate forecast by ETAS at 00:00 UTC on the days: **a** March 17, 2009, **b** April 6, 2009 (1 h and 32 min before the L'Aquila mainshock M_w6.3), **c** April 7, 2009 (the second-largest shock in the Abruzzi region occurred on April 7, 2009, at 17:47 UTC, with M_w5.6) and **d** April 20, 2009. The color scale represents the number of events in units of magnitude larger than 2.0 in cells of 1° .1°per day (From Murru et al. 2014)

where R_o is the background rate density, $\Delta\tau$ is the shear stress change, and A, σ and t_a are parameters of the constitutive law. By fixing some of the parameters based on published results, the authors reduced the number of the model-free parameters, explaining in parallel more thoroughly their physical meaning. The new stochastic model applied to the Japanese seismicity performs as well as the purely stochastic ETAS model. The two models were also tested in Console et al. (2007) with data from California. Despite the poor performance of the model under the constraint of the rate-and-state constitutive law, it is considered that its physical meaning may provide insights into seismogenic processes and should not be rejected.

Another approach focusing on probabilistic aspects is conducted by Iervolino et al. (2014). They analytically combined results of probabilistic seismic hazard analysis (PSHA) and aftershock probabilistic seismic hazard analysis (APSHA) in order to get a seismic hazard integral accounting for mainshock–aftershocks seismic sequences. Their results are particularly interesting from an earthquake engineering perspective since seismic hazard is expressed in terms of occurrence rate causing the exceedance of an acceleration threshold.

Despite the wide variety of purely temporal models and time-independent spatial models, in practice the spatiotemporal models have not been fully exploited, mainly due to the fact that the implementation of such models demands heavy and complicated numerical computations. The concept of epidemic models though has been particularly popular, like the spatiotemporal ETAS model (Ogata 1998) that has been extensively applied in the context of earthquake short-term clustering (Helmstetter and Sornette 2002; Marzocchi et al. 2012; Murru et al. 2014). Another model that has common elements with the ETAS model is the EEPAS-Every Earthquake is a Precursor According to Scale-model. The EEPAS model by Evison and Rhoades (2004) and Rhoades and Evison (2004) is based on predictive scaling relations derived from many examples of the precursory scale increase phenomenon —an increase in the magnitude and occurrence rate of minor earthquakes that precede most major earthquakes on a time scale ranging from months to decades, depending on magnitude. Even though extensive studies were conducted and many relationships between precursory earthquakes and subsequent strong mainshocks have been suggested, regarding the magnitude, time, and location, in practice there are no tools for recognizing precursory earthquakes in advance. In this stochastic forecasting model, the identification of precursory earthquakes is set aside and every event is considered a long-range precursor period taking into account a scale based on its magnitude. The conditional intensity of the EEPAS process has a similar form with the ETAS, as

$$\lambda^*(t,m,x) = \mu\lambda_0(t,m,x) + \sum_{t_i<t} w_i\eta\left(m_i\right)r(M|M_i)f(t-t_i|M_i)g(x-x_i|M_i),$$

where λ_o is a reference rate density, which can be considered as the null hypothesis, e.g., the Poisson model, μ is a parameter that can be considered as the rate of events that are observed without a sequence of precursory earthquakes that can be predicted and η is a function of magnitude. Although the ETAS and the EEPAS models have similar forms of the conditional intensity, they differ in their details. For example, the functions f and g are not based in the Omori formula, which is an indispensable element of the ETAS model. Nevertheless, the weights w_i that are usually set to 1 could be obtained from an initial stochastic declustering that depends on the ETAS model. The EEPAS model has been used in several earthquake catalogs worldwide, e.g., New Zealand and California (Rhoades and Evison 2004; Rhoades 2007), Japan (Rhoades and Evison 2005, 2006) and Greece (Console et al. 2006a, b), and in synthetic catalogs as well (Rhoades et al. 2011).

The aforementioned rate density λ_o is related to the Proximity to Past Earthquakes (PPE). The PPE model, as its name reveals, relies on the proximity to previous shocks, taking into consideration their magnitudes. Most of its characteristics are associated with the forecasting model of Jackson and Kagan (1999). The PPE model gets the form

$$\lambda_{PPE}(t,m,x,y) = g_o(m)h(t,x,y),$$

where

$$g_o(m) = \beta exp\left[-\beta\left(m-m_c\right)\right]\left(m > m_c\right)$$

and

$$h(t,x,y) = \frac{1}{t-t_o}\sum_{t_i<t} h_{eq}(i)$$

where

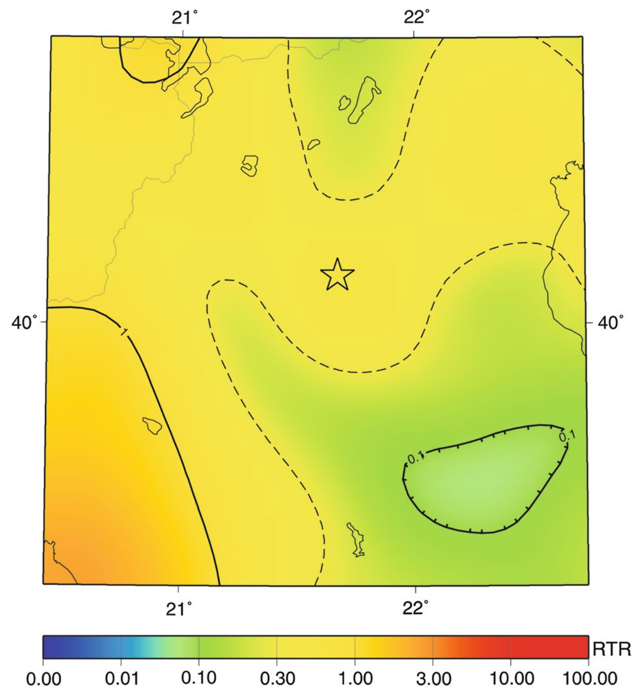

Fig. 6 Average rate of earthquake occurrence for $M>6.35$ over the year 1995 under the EEPAS model, using data up to the end of 1994 in the area of Kozani (Greece). The rate is expressed relative to a reference scale (RTR) in which there is an expectation of 1 earthquake per year exceeding any magnitude m in an area of 1 $10^m km^2$. The epicenter of the M6.6 earthquake of 13 May 1995, 0847:17.0 UT is depicted by a star (From Console et al. 2006a, b)

$$h_{eq}(i) = \frac{a\left(m_i-m_c\right)}{\pi\left(d^2+\Delta_i^2\right)} + s$$

and Δi is the distance from (x, y) to (xi, yi). The parameters β, α, d, and s are to be fitted from data. Here $\beta = bln(10)$, where b is the G–R b–value, α is a normalization parameter, d is a smoothing distance in kilometers, and s is a spatially uniform background rate (occurrence per day per kilometer squared) that accounts events occurring far from the previous ones. As a result, the earthquake occurrence–rate density is high near the locations of past earthquakes and low far away from all past earthquakes. Regarding the magnitude, the larger the nearby past earthquakes are, the greater is the rate density. The PPE and EEPAS model have been candidate models in the CSEP Earthquake Forecast Testing Centers in New Zealand and California (Gerstenberger and Rhoades 2010; Rhoades and Stirling 2012; Schneider et al. 2014; Rhoades et al. 2018). An example of the rate of earthquake occurrence given by the EEPAS model is shown in Fig. 6 (From Console et al. 2006b).

Another candidate spatiotemporal model of earthquake occurrence is the double branching model by Marzocchi and Lombardi (2008), which is applied in two steps. The first step includes the application of the ETAS model so that triggered events are removed from the catalog. The next step consists of the reapplication of the model—the same or one with high resemblance—to the rest of the seismicity so that the long-term clustering is described.

Summary

The approaches for modeling and forecasting seismogenesis revealed that understanding earthquake phenomena which are complex and trying to predict them could be achieved by developing and applying progressively sophisticated and refined stochastic models. Their development and application could bridge the gap between the underlying physics and the small amount of the available data.

Selecting the most suitable model among all the competing ones is not a trivial issue. For that reason, rigorous tests and experiments should be implemented. In that direction, a collective international attempt has been made feasible in the Collaboratory for the Study of Earthquake Predictability (CSEP) experiment, for several regions all over the world. Their goal, since its inception in California in 2007, is to test alternative scientific hypotheses, their predictive abilities and consequently improve seismic hazard assessment.

The innovative concept of CSEP is that scientists are requested to submit their models for testing in pre-agreed datasets and standardized statistical tests. In that way, full independence is guaranteed and the comparisons between the models are objective (Schorlemmer et al. 2018). The next steps of CSEP include tests of fault-based forecasts where finite-fault information is provided instead of just testing the locations of hypocenters, forecasts based in simulations, tests where earthquake clustering is better approximated, and tests of ground-motion measures that achieve direct probabilistic seismic hazards assessments (Michael and Werner 2018).

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