

Article

Exceedance Probabilities for Large Earthquakes from DIY Local Earthquake Ensemble Nowcasting and Forecasting: Magnitude, Natural Time, and Calendar Time

John B. Rundle ^{1,2,3,*} , Ian Baughman ¹, Andrea Donnellan ^{3,4}, Lisa Grant Ludwig ⁵ , Geoffrey Fox ⁶ and Kazuyoshi Nanjo ⁷ 

¹ Departments of Physics and Earth and Planetary Sciences, University of California, Davis, CA 95616, USA; itbaughman@ucdavis.edu

² Santa Fe Institute, Santa Fe, NM 87501, USA

³ Jet Propulsion Laboratory, Pasadena, CA 91109, USA; andread@purdue.edu

⁴ Department of Earth, Atmospheric, and Planetary Sciences, Purdue University, West Lafayette, IN 47907, USA

⁵ Department of Population Health and Disease Prevention, University of California, Irvine, CA 92697, USA; lgrant@uci.edu

⁶ Department of Computer Science, Biocomplexity Institute, University of Virginia, Charlottesville, VA 22901, USA; vxj6mb@virginia.edu

⁷ Global Center for Asian and Regional Research, University of Shizuoka, Shizuoka 420-0839, Japan; nanjo@u-shizuoka-ken.ac.jp

* Correspondence: jbrundle@ucdavis.edu

Abstract

In this paper, we describe a method for computing calendar time forecasts in a local area for large earthquakes of a target magnitude M_T using a count of small earthquakes in the magnitude range M_S to M_T in the area. Using the idea that the Gutenberg–Richter (GR) relation is valid throughout the surrounding region, we define an ensemble of earthquakes in larger surrounding regions to be used in computing the forecast. What follows is simple data mining. “Local” is defined by the probability of a large earthquake occurring within a defined circle of arbitrary radius surrounding a point of interest. The main (and for that matter, the only) assumption for all these works is that the GR magnitude–frequency relation holds. The method has significant skill, as defined by the Receiver Operating Characteristic (ROC) test, which improves as the time since the last major earthquake increases. The probability is conditioned on the number of small earthquakes $n(t)$, with $M \geq M_S = 3.49$, that have occurred since the last large earthquake. The probability is computed directly as the Positive Predictive Value (PPV) associated with the ROC curve. The method is compared with the UCERF3 forecasts for the UCERF3-defined geographic boxes centered on Los Angeles and San Francisco and serves as an indicative benchmark. The method is then applied to a 125 km radius circular area around Los Angeles, California, following the 17 January 1994 magnitude M6.7 Northridge earthquake, and short-term forecasts (1-year and 5-year) are computed. We further apply the method to six additional geographic regions with validation by comparison with an estimate of the time-independent conditional Poisson probability. These regions are Athens, Greece; Chengdu, China; Jakarta, Indonesia; Lima, Peru; Santiago, Chile; and Tangshan, China.

Keywords: earthquakes; nowcasting; forecasting; exceedance probabilities



Academic Editor: Riccardo Caputo

Received: 24 April 2026

Revised: 15 June 2026

Accepted: 17 June 2026

Published: 22 June 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)

[Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

1.1. Ensemble Earthquake Forecasting (EEF)

This paper develops a new method for earthquake forecasting using an ensemble approach. It is the third of a three-part series introducing methods for computing local earthquake forecasts and associated probabilities of future large earthquakes from local earthquake nowcasts. The first paper [1] detailed a method to compute local forecasts for a fixed future natural time interval, where natural time is the count of small earthquakes since the last large earthquake. The second paper [2] extended these methods to calendar time forecasts using an ensemble-of-regions approach. Here, the local region of interest, a circle of radius r_C surrounding a central geographic point of interest, is enclosed by an expanding series (ensemble) of regions.

To summarize our results:

- Local ensemble probabilities for large earthquakes are computed using only counts of small earthquakes in an expanding ensemble of rectangular regions. These small earthquakes cover a magnitude $3.49 \leq M \leq 6$ range of small to moderate quakes. Due to the rapid falloff in the GR relation, the count of such earthquakes is dominated by those at the low end, so we use the term “small earthquakes” to describe them in this paper. Our results are not sensitive to the precise magnitude cuts used.
- Ensemble exceedance probabilities for magnitude and earthquake occurrence time can be computed for evaluating risk profiles.
- To test the basic assumption of uniformity of statistics, a nowcast transform can be defined to adjust the regional statistics to enforce uniformity within the ensembles of events.
- The method is then validated/benchmarked by comparison with the accepted current USGS forecasts.
- Applications of the method are provided for a series of locations in California and worldwide, with the worldwide applications compared with the conditional Poisson (exponential) probability of occurrence.

1.2. Earthquake Nowcasting

Previous papers have developed several techniques for earthquake nowcasting. The nowcasting approach is based on “natural time”, which is defined as counts of small earthquakes [3–6]. Natural time is the time scale that is relevant to the system dynamics, so earthquake nowcasting uses natural time to track the progression of the fault system through its cycle of large earthquake activity. The term “nowcasting” is used in the same sense as for weather and economic nowcasting [7,8], tracking the current state of a system in the recent past, current time, and near future. Methods to produce earthquake nowcasts are the subject of many previous papers [7–39]. Although the framework presented here is primarily statistical, it rests on a physical, geomechanical foundation. The accumulation of small earthquakes (natural time) acts as a physical proxy for continuous regional tectonic loading and strain accumulation. As the fault system progresses through its seismic cycle, microseismicity reflects localized yielding, systematically tracking the fault network’s macroscopic approach toward the critical stress threshold required to trigger a large target earthquake.

The nowcasting method is applied to a small circle of arbitrary radius surrounding a point of interest, typically a city. Computing the probability then involves a data mining phase using an expanding series or ensemble of larger rectangular regions surrounding the circle. These regions then comprise the ensemble for the method. Each member of the ensemble contains a number of earthquake “cycles”, which begin and end on earthquakes larger than a target magnitude M_T . Each cycle contains a number of “small” earthquakes

with magnitude in the range M_S to M_T . The similarity of the Gutenberg–Richter statistics for the local region and the surrounding ensemble regions is used to construct a time scaling for the times in the ensemble cycles.

After time scaling the calendar forecast times for the ensemble members, we then consider each cycle of activity in a given ensemble. Collections of time-scaled cycles of activity that have fewer small events than the number in the circle are considered to represent a set of might-have-been past histories for activity in the circle. Collections of time-scaled cycles of activity that have more small events than the number in the circle are considered to represent a set of possible future activity for the circle.

We apply our forecast methods to a circular region of radius 125 km surrounding Los Angeles, CA, using a target magnitude $M_T = 6$ and small earthquakes with $3.49 \leq M \leq 6.0$. The most recent large earthquake in the circle was the Northridge earthquake, with magnitude $M = 6.7$, which occurred on 17 January 1994.

The choice of circle radius is arbitrary; that is to say, it is not a “model parameter”, but instead a “user choice”. We use a rule of thumb that the radius should be at least twice the linear dimension of the aftershock zone of the previous large earthquake in the circle. All earthquake forecasts in the literature choose one of the following: (a) a spatial region such as a country, a state, or a local region; or (b) a given earthquake fault or set of faults. The forecast then applies only to that particular choice. Note that the quantitative analysis in [38] of an appropriate circle radius for similar earthquake magnitudes in Greece arrives at a radius of 125 km. An additional criterion for the choice of radius is the “radius of significant ground shaking” for a given magnitude, for example, the distance at which one might experience Mercalli Intensity VI (PGA ~ 0.1 g) shaking. This distance is about 100–150 km for an $M_T = 6$ earthquake, which is our minimum size for the forecast [40,41].

Examples of the data for a circular region of radius 125 km around Los Angeles, CA, and a selection of the ensembles is shown in Table 1. Here, Min/Max Cycle Length is the minimum/maximum number of small earthquakes among the cycles for that region size. Total Small EQ entry is the total number of small earthquakes in the catalog for the circle or ensemble member since 1980 for the range $M \geq 3.5$. Least squares fits in each ensemble member are used to compute the Gutenberg–Richter b -values. The range of magnitude values used for computing the b -values is between $M = 3.5$ and $M = 6.5$.

Table 1. Statistical data for selected ensemble members for cycles between successive magnitude $M \geq 6$ earthquakes from 1980.0–present. Min/Max Cycle Length is the minimum/maximum number of small earthquakes among the cycles for that region size. Total Small EQ entry is the total number of small earthquakes in the catalog for the circle or ensemble member since 1980 for the range $M > 3.5$. Least squares fits in each ensemble member are used to compute the Gutenberg–Richter b -values. The range of magnitude values used for computing the b -values is between $M = 3.5$ and $M = 6.5$.

		Ensemble Number						
Region	125 km LA Circle	1	5	10	15	20	25	30
		3.6° × 3.6° Rectangle	4.0° × 4.0° Rectangle	4.5° × 4.5° Rectangle	5.0° × 5.0° Rectangle	5.5° × 5.5° Rectangle	6.0° × 6.0° Rectangle	6.5° × 6.5° Rectangle
Total Small EQ	600	6286	6657	7345	7803	8026	8192	8777
Number Cycles	-	22	24	27	29	32	33	41
Min Cycle Length	-	15	10	10	10	2	6	7
Max Cycle Length	-	657	797	800	825	730	755	798
b-value	0.93 ± 0.02	0.96 ± 0.01	0.96 ± 0.01	0.97 ± 0.01	0.98 ± 0.01	0.96 ± 0.01	0.97 ± 0.01	0.94 ± 0.01

The next step involves computation of the ROC curve for each member of the ensemble, a plot of the True Positive Rate (TPR) vs. the False Positive Rate (FPR) [42,43]. Once we are in possession of these curves, we compute the ensemble mean curve and its standard deviation. The area under the ROC curve (AUROC, or “skill”) can be interpreted as the ability of a model to discriminate between, or to correctly classify, different categories of events. In our case, an event is the occurrence of a major earthquake vs. non-occurrence [42,43]. The method then uses a simple data mining method on the longer earthquake cycles to compute the probability of future events.

2. Materials and Methods

2.1. Scaled Similarity

These ensemble regions are assumed to exhibit Gutenberg–Richter magnitude–frequency (GR) statistics that are the same as or similar to those in the circular region. This assumption can be stated as an assumption of “scaled similarity”; when the temporal statistics of the members of the ensemble are appropriately scaled in time, the members can be regarded as statistical “copies” of the earthquakes in the circular region. While the broad consistency of b -values across the ensemble members supports this space-for-time substitution, this approach implicitly relies on a degree of ergodicity. We acknowledge that tectonic and structural heterogeneities—such as spatial variations in crustal rheology, fault maturity, and local stress orientations—limit the strict validity of this assumption. Consequently, the scaled similarity across expanding spatial regions serves as a practical statistical approximation rather than an exact physical equivalence.

The specific form of the GR law that is used here is:

$$N = 10^{b(M_T - M_S)} \quad (1)$$

where N is the ratio of the number of earthquakes with magnitude larger than M_S , to the number larger than the target earthquake M_T , and b is a parameter that is usually near $b = -1$ but can typically vary by approximately ± 0.05 . We will apply Equation (1) in the following to the case where there is one quake of magnitude M_T or greater. Note that this equation shows that the average magnitude of all quakes larger than $M_S = 3.49$ is approximately 3.92, quantifying our terminology of “small earthquakes”.

Step 1: The Nowcast Function and Earthquake Cycles

The first step in the analysis is to introduce a nowcast function $\Phi(n)$:

$$\Phi(n) = 1 - e^{-(n/N)} \quad (2)$$

where n is the number of small earthquakes of magnitude M_S or larger since the last large earthquake of target magnitude M_T [1]. Equation (2) was chosen as a consequence of the observation [44], which has been validated many times by others [8]; aside from aftershock clustering, earthquakes occur randomly in time with Poisson statistics. In addition, Refs. [7,8] has shown that Equation (2) generally characterizes the interval statistics between large earthquakes M_T . Note that in the following figures, we plot the nowcast value as ranging between [0%, 100%] rather than [0, 1].

We begin by considering a circular region of radius 125 km surrounding a point of interest, in this case, the city of Los Angeles, CA [1,2,7]. In Figure 1, a region of radius 125 km around the city of Los Angeles is shown as a blue circle. In the middle, green bars show the histogram of the number of small earthquakes between large earthquakes. The solid red stair-step line is the Cumulative Distribution Function (CDF) corresponding to

the histogram. Magenta dashed lines are the standard deviations from the CDF, computed using a bootstrap method.

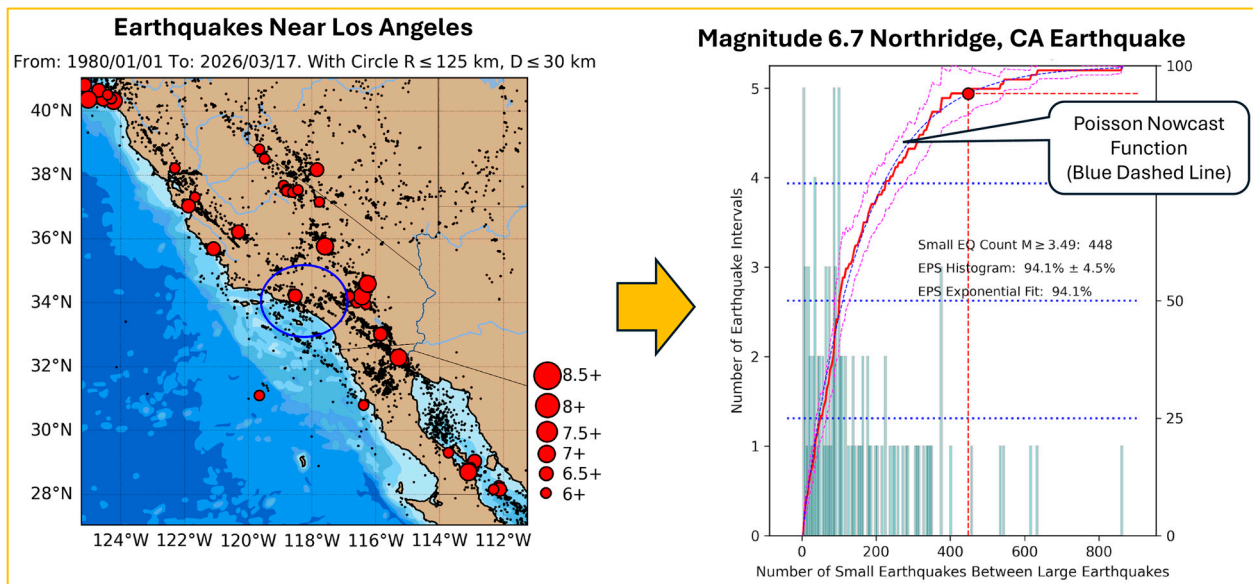


Figure 1. Left: Regional seismicity (small dots) from 1 January 1980 to 17 March 2026 used in this paper, showing the small earthquakes $3.49 \leq M < 6.0$ between large $M \geq 6.0$ large earthquakes, shown as red circles. A region of radius 125 km around the city of Los Angeles is shown as a blue circle. Right: Green bars show the histogram of the number of small earthquakes between large earthquakes. The solid red stair-step line is the Cumulative Distribution Function (CDF) corresponding to the histogram. Magenta dashed lines are the standard deviations from the CDF, computed using a bootstrap method. The red dot is the current count (=448) of small earthquakes in the circular region since the 17 January 1994 Magnitude 6.7 Northridge, CA, earthquake. Current count corresponds to a CDF/nowcast Poisson value of 94.1%. Blue dashed line is the Poisson CDF, which we use as the “nowcast function”, and is based on the average (Gutenberg–Richter) number of small earthquakes in the region (see Equation (1) in the text). The blue dotted horizontal lines are just 25%, 50% and 75%. EPS stands for Earthquake Potential Score.

The red dot is the current count (=448) of small earthquakes in the circular region since the 17 January 1994 Magnitude 6.7 Northridge, CA, earthquake. Current count corresponds to a CDF/nowcast Poisson value of 94.1%. The blue dashed line is the Poisson CDF, which we use as the “nowcast function”, and is based on the average (Gutenberg Richter) number of small earthquakes in the region, Equation (1). On the right is the GR relation for the larger region and the circle, where it can be seen that the two b -values are nearly the same.

2.2. Nowcast Function and the Ensemble Method

In the steps below, we outline the ensemble method in more detail. Figure 2 shows an ensemble of expanding rectangular regions. The last major earthquake within this circle was the magnitude $M_{6.7}$ Northridge, CA, earthquake on 17 January 1994. We wish to compute the probability of the next large earthquake of target magnitude $M_T \geq 6$ occurring within the circular region, whose radius was chosen mainly because it is about twice the radial dimension of the aftershocks of the Northridge earthquake. On the left, a series of expanding regions (white rectangles) is constructed surrounding the circular region. On the right, we use the nowcast function (2) to build a time series of nowcast earthquake cycles for each region in the ensemble using the small earthquakes with magnitude ranging from $M_S = 3.49$ and M_T between the large target earthquakes, $M_T \geq 6.0$. The results are not

sensitive to the exact choices of M_S and M_T , but in this paper, M_S is 3.49 for all California results and 4.0 for locations outside the USA to ensure reliable data. M_T is always 6.0.

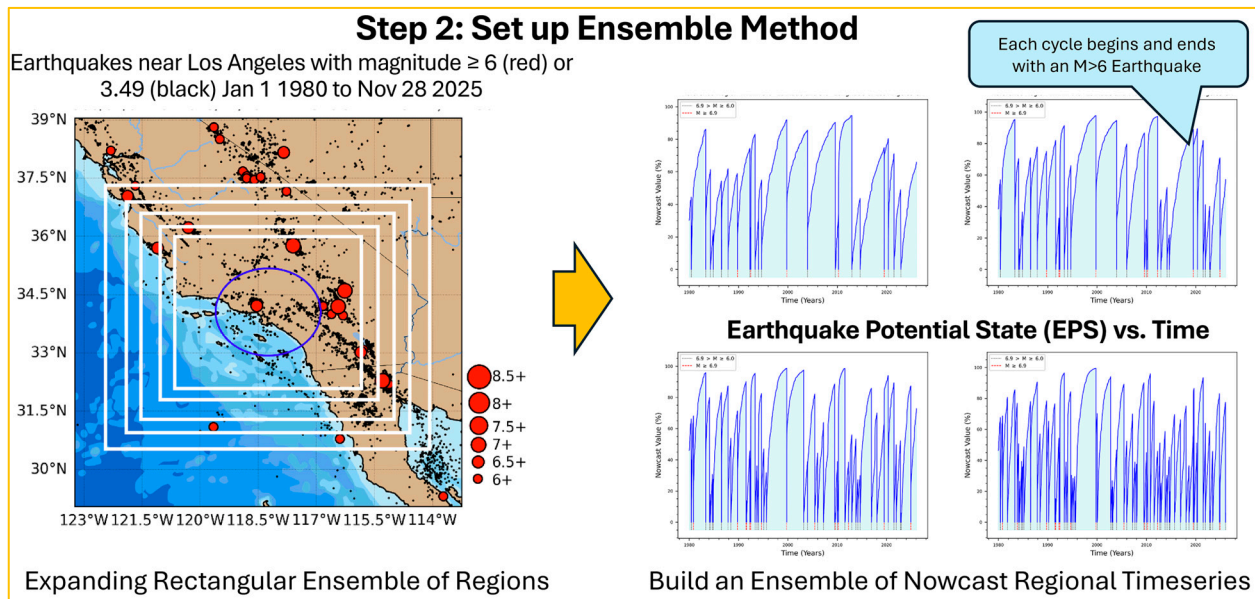


Figure 2. Schematic illustration of the ensemble method. **Left:** A series of expanding regions (white rectangles) is constructed surrounding the circular region. **Right:** Using the nowcast function (Equation (2)), a time series of nowcast earthquake cycles for each region in the ensemble is constructed using the small earthquakes $M_S = 3.49 \leq M \leq M_T$ between the large target earthquakes $M_T \geq 6.0$. Each cycle in the four figures on the right begins and ends with a magnitude $M \geq 6$ earthquake.

These time series represent the ensemble of time series that we analyze using Receiver Operating Characteristic (ROC) methods that will be used to build the Positive Predictive Value (PPV), which is the forecast for each ensemble member.

2.2.1. Step 1: Construct the Ensemble of Cycles

Using Equation (2), build a series of “large earthquake cycles” in the ensembles, shown schematically in Figure 2, surrounding the circular region and centered on Los Angeles. Each of the cycles begins and ends at the time of a target earthquake. So, an ensemble member with N_{ENS} large earthquakes will have $J = N_{ENS} - 1$ cycles by this definition. These cycles of activity represent the data set for the simple data mining application.

The i th ensemble member will have a set of J cycles $n_{i,j}$ denoted by C_i :

$$C_i\{n_i\} = \{n_{i,1}, n_{i,2}, n_{i,3}, \dots, n_{i,J}\} \quad (3)$$

Here, $n_{i,j}$ is the number of small earthquakes in the j th cycle of the i th ensemble.

2.2.2. Step 2: Scale the Forecast Time for Each Ensemble Member

Build conditional ROC curves for each member of the ensemble using the following method, then compute the mean ROC curve from the ensemble ROC curves. The curves are conditioned on the number of small events that have occurred prior to calculation of the ROC curve.

We choose a forecast time of interest $T_{F,C}$ for the next target earthquake in the circular region. The number of small events in the circle will be designated as n_C , and the corresponding rate of small earthquake occurrence within the circle is designated as R_C .

Clearly, each member of the expanding ensemble will have a larger number of small events than the number of small events in the circle. The i th ensemble member will have a total number n_i of small earthquakes and a corresponding rate of occurrence R_i .

We then scale the forecast time interval for each member of the ensemble, $T_{F,i}$, according to [1,2]:

$$T_{F,i} = \left(\frac{R_C}{R_i} \right) T_{F,C} \quad (4)$$

2.2.3. Step 3: Build Conditional Receiver Operating Characteristic (ROC) Curves

To build the conditional ROC curves for each of the ensembles, we adopt a set of threshold values for the time series amplitudes [12–16]. For each ensemble member, we classify all points on the nowcast time series by sweeping the threshold values over all amplitudes of the time series on the interval $[0, 1]$.

We start by selecting an arbitrary threshold value τ . Given a small event occurring at time t , we ask if the nowcast value of that event is above or below the threshold. We also ask if the next target earthquake M_T occurs after time t but within the time interval $t + T_{F,i}$, where again, $T_{F,i}$ is the scaled forecast time for that ensemble member. Classification is then given by:

- TP, if the nowcast value is above the threshold τ and the next target earthquake occurs within $t + T_{F,i}$.
- FP, if the nowcast value is above the threshold τ and no earthquake occurs within interval $t + T_{F,i}$.
- FN, if the nowcast value is below the threshold τ and the next target earthquake occurs within interval $t + T_{F,i}$.
- TN, if the nowcast value is below the threshold τ and no target earthquake occurs within interval $t + T_{F,i}$.

It should be emphasized that the conditional ROC diagram is conditioned on the current number of events in the circle. For example, if the current number of small earthquakes in the circle is, for example 100, then no cycles of length less than 100 are used in the classification.

Classifying all points on an ensemble time series will then produce a confusion matrix, or contingency table, composed of the quantities TP, TN, FP, and FN. We should also explicitly note that these quantities are functions only of the threshold values, τ , so that we have $TP(\tau)$, $TN(\tau)$, $FP(\tau)$, and $FN(\tau)$. Conditional ROC curves for each member of the ensemble are computed, and the mean and standard deviation of the curves are computed. From each confusion matrix, we compute the True Positive Rate (TPR) and the False Positive Rate (FPR):

$$\begin{aligned} \text{TPR} &= \text{TP} / (\text{TP} + \text{FN}) \\ \text{FPR} &= \text{FP} / (\text{FP} + \text{TN}) \end{aligned} \quad (5)$$

Examples of conditional ROC diagrams are shown in Figure 3. Cyan curves represent the ROC curves for the ensemble members, the red curve is the ensemble mean, and the dashed curves are the standard deviations. In Figure 3a, the ROC diagram is computed after no small earthquakes have occurred. In Figure 3b, the ROC diagram is computed after 150 small earthquakes have occurred. In Figure 3c, the ROC diagram is computed after 300 small earthquakes have occurred. In Figure 3d, the ROC diagram is computed after 448 small earthquakes have occurred, which is the number in the circle to date.

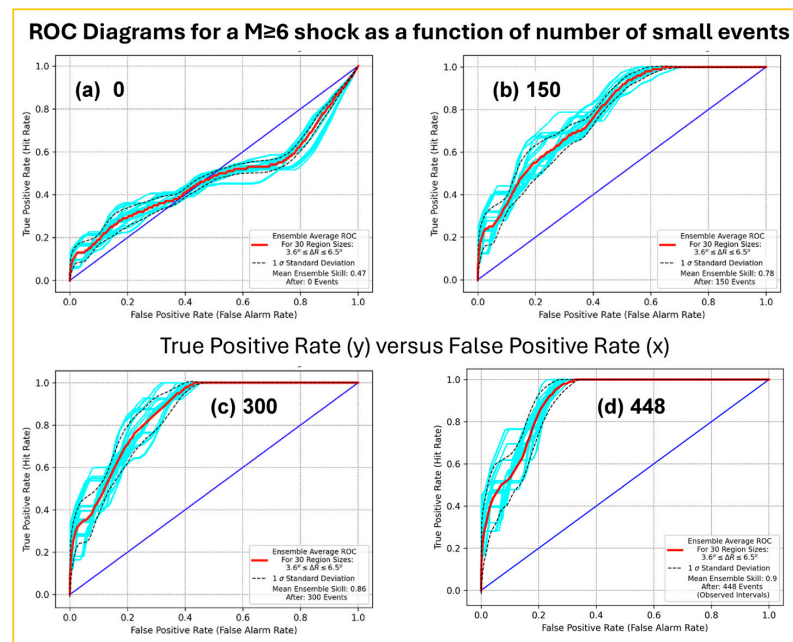


Figure 3. Conditional Receiver Operating Characteristic (ROC) diagrams for an ensemble of 30 regions from 3.6° to 6.5° surrounding Los Angeles, CA, at 0.1° interval half-widths, with a forecast time of $T_F = 5$ years. ROC diagrams showing true vs. false positive ratios computed after no small earthquakes have occurred (a), after 150 small earthquakes have occurred (b), after 300 small earthquakes have occurred (c), and after 448 small earthquakes have occurred (d), which is the number in the circle to date. The diagrams are conditional because only cycles with more events than the designated number (0, 150, 300, 448) of events are used to compute the ROC curves. Cyan curves are for the various ensemble members. The red curve is the mean value, and dashed curves are the 1 standard deviation curves. The blue diagonal line is the no-skill line. The skill for the curves are, respectively, 0.47, 0.78, 0.86, and 0.90, showing that skill improves progressively as the earthquake cycle proceeds.

It is important to interpret the progressive improvement of conditional ROC skill with caution as it involves an element of retrospective conditioning. Because the ROC diagrams are constructed using historical catalog data where the target outcomes are already known, there is a potential for optimistic bias in the apparent predictive skill. To fully quantify the operational limits of this skill without retrospective leakage, the method must ultimately be evaluated through prospective, out-of-sample forward testing.

2.2.4. Step 4: Compute Positive Predictive Value (PPV) from the ROC Curves

Once the conditional ROC curve is computed for a member of the ensemble, the Positive Predictive Value (PPV) is then computed:

$$\text{PPV} = \text{TP} / (\text{TP} + \text{FP}) \quad (6)$$

The PPV value is the probability of a future large earthquake of target magnitude M_T during the forecast interval $T_{F,C}$.

To compute the PPV values (probabilities) at the times of the small events following the last large event in the circle, we use as threshold values τ the nowcast values $\Phi(n_C)$ for the small events in the circle. So, if there are 100 small earthquakes within the circle since the last large earthquake, we compute 100 values for $\Phi(n_C)$ and use these as our threshold set $[\tau(n_C)] \equiv [\Phi(n_C)]$. Note that each of these small earthquakes has a calendar time t .

Each of these small earthquakes in the circle then has a defined nowcast value, an index, and an occurrence time, all of which are associated with the small event. Again, note

that the TP, FP, TN, and FN are functions of the threshold only, which in this special case is the event nowcast value. Since the nowcast value is also a threshold, this association allows us to identify specific event sequence numbers and event times with a PPV value.

Figure 4 shows examples of calendar forecasts of this type for both 1-year and 5-year time scales. The figures represent plots of PPV, the probability of a future $M \geq 6$ earthquake, as a function of time since the $M_{6.7}$ Northridge, CA, earthquake on 1/17/1994. In Figure 4a, the ensemble size = 30, and the forecast time interval $T_F = 1$ year. In Figure 4b, the ensemble size = 60, and the forecast time interval $T_F = 1$ year. In Figure 4c, the ensemble size = 30, and the forecast time interval $T_F = 5$ years. In Figure 4d, the ensemble size = 60, and the forecast time interval $T_F = 5$ years. The cyan curves are for the various ensemble members. The red curve is the mean of the cyan curves, the ensemble probability, and dashed curves are the one-standard deviation curves.

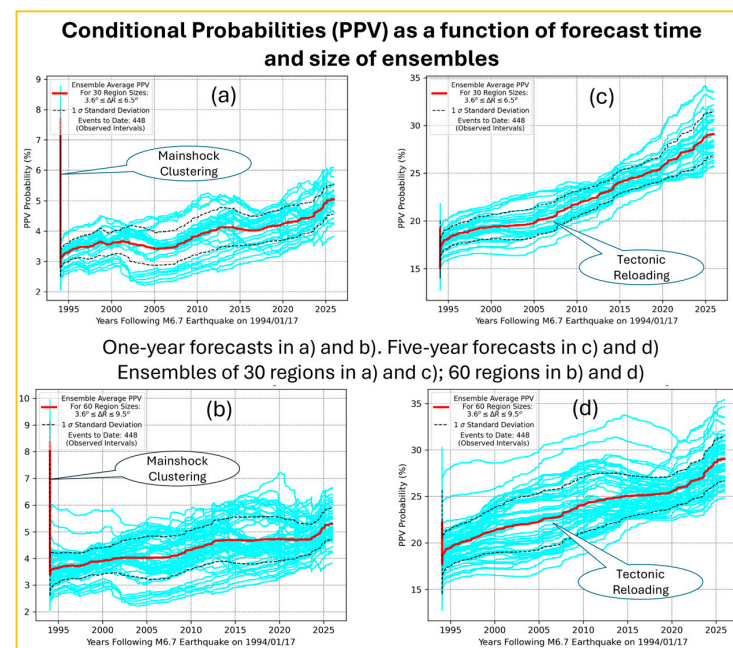


Figure 4. Plots of PPV, the probability of a future $M \geq 6$ earthquake, as function of time since the $M_{6.7}$ Northridge, CA, earthquake on 17 January 1994. (a) Ensemble size = 30, forecast time interval $T_F = 1$ year. (b) Ensemble size = 60, forecast time interval $T_F = 1$ year. (c) Ensemble size = 30, forecast time interval $T_F = 5$ years. (d) Ensemble size = 60, forecast time interval $T_F = 5$ years. Cyan curves are for the various ensemble members. The red curve is the mean of the cyan curves, the ensemble probability, and dashed curves are the 1-standard deviation curves. In figures (a,b), probability immediately after the mainshock is high, indicating a tendency for mainshock clustering. In figures (c,d), tectonic reloading over time following the Northridge earthquake is the primary process that can be seen.

In Figure 4a,b, the probability immediately after the mainshock is high, indicating a tendency for mainshock clustering. In Figure 4c,d, an increase in probability due to tectonic reloading over time following the Northridge earthquake is the primary process that can be seen.

2.3. Conditional Exceedance Curves

We now compute conditional exceedance curves (survivor distributions), conditioned on the number of small earthquakes that have occurred prior to computation of the probabilities.

2.3.1. Magnitude Exceedance

To build a magnitude exceedance probability, we note that all the cycles in an ensemble are terminated (and begin) with a magnitude $M \geq M_T$. Thus, we can build a set consisting of the next, or terminating, magnitudes $M_{i,j}$ for each interval $n_{i,j}$:

$$C_i\{M_i\} = \{M_{i,1}, M_{i,2}, M_{i,3}, \dots, M_{i,J}\} \quad (7)$$

Considering both $C_i\{M_i\}$ and $C_i\{n_i\}$, we then build a combined set of intervals and magnitudes:

$$\begin{aligned} C\{M\} &= \bigcup_{i,j} \{M_{i,1}, M_{i,2}, M_{i,3}, \dots, M_{i,J}\} \\ C\{n\} &= \bigcup_{i,j} \{n_{i,1}, n_{i,2}, n_{i,3}, \dots, n_{i,J}\} \end{aligned} \quad (8)$$

where the $\bigcup_{i,j} \{\}$ indicates the union of all sets of ensemble intervals and magnitudes into a single large set.

Once we have these two large sets, we can construct the conditional survivor distributions (exceedance probabilities) for terminating magnitudes. In Figure 5, conditional exceedance curves are shown for several examples of natural times (small event counts), for 0 small events (immediately after the last large earthquake), for 448 small events (the current count in the circular region), and for the current-plus-mean-projected number of small events in the circular region. The mean projected number is the average number expected until just before the next large earthquake. This mean projected number is computed by finding the mean of all intervals larger than the current number, 448, minus the current number. Note that a light smoothing has been applied to these curves.

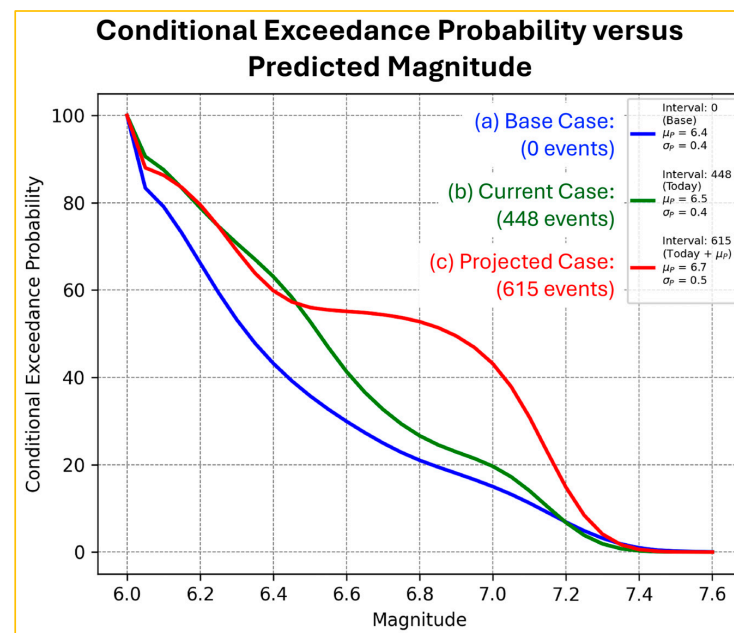


Figure 5. Conditional exceedance probabilities for magnitude of the terminating target earthquake $M \geq M_T$ after a number of small earthquakes have occurred. (a) Base case, just after the last large earthquake, in which no small earthquakes have occurred yet. (b) Current case for the number of small earthquakes (448) that have occurred. (c) A future time at which 615 small earthquakes have occurred. This is for an ensemble of 30 regions, from 3.6° to 6.5° surrounding Los Angeles, CA.

2.3.2. Magnitude Exceedance for 25%, 50%, and 75% Probability

Figure 6 analyzes this conditional exceedance data further by computing the 25%, 50% (median), and 75% exceedance probabilities as a function of the number of small events that

have occurred. Note the blue vertical line, which indicates the number of small earthquakes that have occurred to date, which is 448. As more small earthquakes occur in the future, the magnitude exceedance probabilities, particularly for the median (50%) and 25% level, will begin to increase sharply.

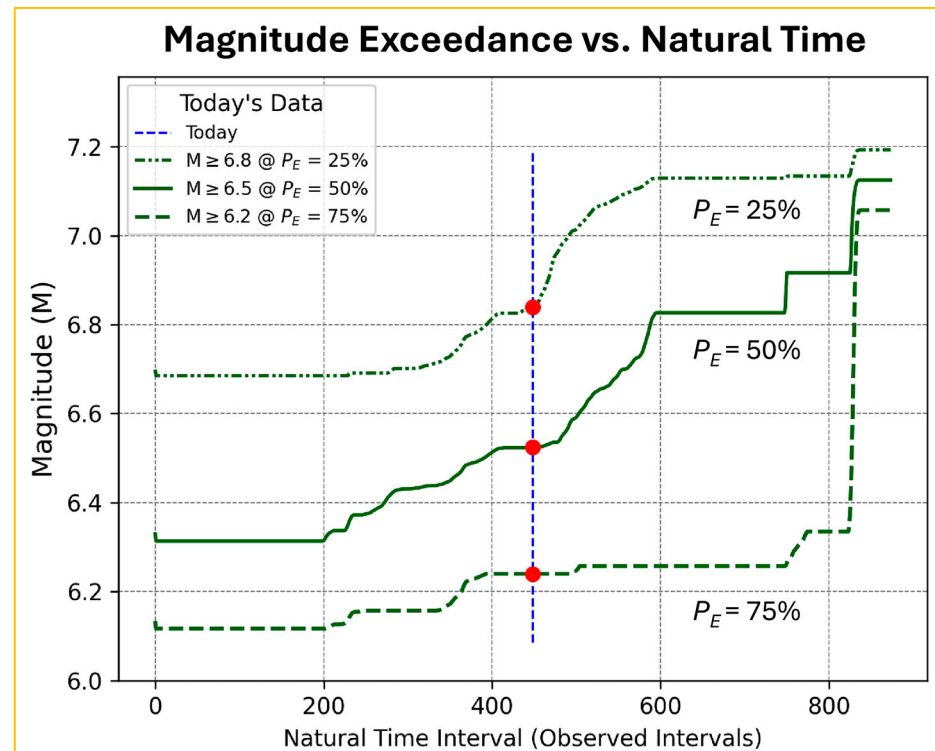


Figure 6. Plot of expected cycle terminating magnitude vs. natural time (small event counts) for 25%, 50%, and 75% values of exceedance probability. This is for an ensemble of 30 regions from 3.6° to 6.5° surrounding Los Angeles, CA.

2.3.3. Calendar Time Exceedance

To compute the calendar exceedance, or waiting time until the next large earthquake M_T , we first create the set $C(\Delta T_i)$ of combined ensemble time intervals ΔT_i corresponding to the natural time intervals in Equation (8):

$$C\{\Delta T\} = \bigcup_{i,j} \{\Delta T_{i,1}, \Delta T_{i,2}, \Delta T_{i,3}, \dots, \Delta T_{i,J}\} \quad (9)$$

Next, we scale the time intervals $\Delta T_i \rightarrow \Delta T'_i$ using the inverse of the scaling factor in Equation (4):

$$\tilde{\Delta T}_{i,j} = \left(\frac{R_i}{R_C} \right) \Delta T_{i,j} \quad (10)$$

leading to:

$$C\{\tilde{\Delta T}\} = \bigcup_{i,j} \left\{ \tilde{\Delta T}_{i,1}, \tilde{\Delta T}_{i,2}, \tilde{\Delta T}_{i,3}, \dots, \tilde{\Delta T}_{i,J} \right\} \quad (11)$$

Using the sets (8) and (11), we can then construct the conditional exceedance curves for the waiting times, both in natural and calendar times.

2.4. Testing the Method

Now, we test the results of the ensemble method and explore ways to build ensemble forecasts using two additional ideas. These involve the following:

1. We introduce a “nowcast transform” to test the assumption of scaled similarity of the GR statistics in the ensemble.
2. We filter cycle intervals at the 95% confidence level to test an assumption that outliers may determine the statistics.

2.4.1. Nowcast Transform

We define this simple method to test the assumption that the statistics of the ensemble members produce a stable forecast result and to examine the assumption that the statistics of the ensembles being similar to the circle are reasonable.

Using Equation (2), we compute the nowcast value for a typical interval in ensemble i :

$$\Phi(n_{i,j}) = 1 - e^{-(n_{i,j}/N_i)} \quad (12)$$

where the scale N_i for ensemble member i is computed from Equation (1):

$$N_i = 10^{b_i(M_T - M_S)} \quad (13)$$

and where b_i is the b -value for ensemble member i .

To compute the transformed intervals $n'_{i,j}$, we invert Equation (2) by making the equivalence $\Phi(n_{i,j}) = \Phi(n'_{i,j})$ and using the statistics of the circular region:

$$n'_{i,j} = -N_C \log[1 - \Phi(n_{i,j})] \quad (14)$$

and where b_C and N_C represent the statistics of the circle:

$$N_C = 10^{b_C(M_T - M_S)} \quad (15)$$

This process ensures that the transformed ensembles have the same b -value, b_C , as the circle. Thus, the GR interval statistics of the ensembles are the same as those of the circular region.

But in altering the values of the $n_{i,j}$ intervals, we also need to consider the times at which these transformed events occur. There are two cases, one in which $n_{i,j} > n'_{i,j}$ and another in which $n'_{i,j} > n_{i,j}$. We have therefore developed a simple algorithm to assign the small event times for the small events in the intervals:

- For the case $n_{i,j} > n'_{i,j}$, we choose event times in $n_{i,j}$ at random and remove a sufficient number of these. Continue until the necessary number of times have been removed.
- For the case $n'_{i,j} > n_{i,j}$, we pick two neighboring times randomly, find the mean of these two times, and insert that mean time between the two chosen times. Continue until the necessary number of times have been assigned.

A major feature of this simple algorithm is that the basic structure of the event times is preserved. Where times are densely clustered, as in aftershock intervals, proportionately more times are added or removed. Where times are sparse, as when quiescence prevails, fewer times are added or removed. Thus, changes to the temporal density of small event times is proportional to the original density of times. Other algorithms are clearly also possible.

As a final point, since the nowcast transform alters the number of small events in an ensemble, the scaled forecast time must also be further scaled by modifying Equation (4) as:

$$T_{F,i} = \left(\frac{R_C}{R'_i} \right) T_{F,C} \quad (16)$$

2.4.2. Filtering the Earthquake Cycles

In the filter method, we consider the set of intervals $C\{n\}$ from Equation (8). We compute the mean μ and standard deviation σ of the intervals and reject any intervals that are larger than a value $\mu + 2\sigma$ corresponding to the 95% confidence limit. From that point, we repeat the analysis from the above.

3. Results

With these considerations, we can now calculate the ROC curves, the PPV calendar time forecasts, and exceedance curves for the original ensembles, the transformed ensembles, and the filtered ensembles.

3.1. Examples of Nowcast and Filtered Calculations

Figure 7 shows plots of the PPV curves for the original intervals, the filtered intervals, and the nowcast transformed intervals. The plot for the original intervals (Figure 8 left) repeats a plot from Figure 4 for convenience of comparison. The results show that the final value of PPV for the original intervals are the smallest of the three, which are in order from left to right, 29%, 35%, and 43%. While generally consistent, the three plots should be viewed as alternative views of the forecast probabilities.

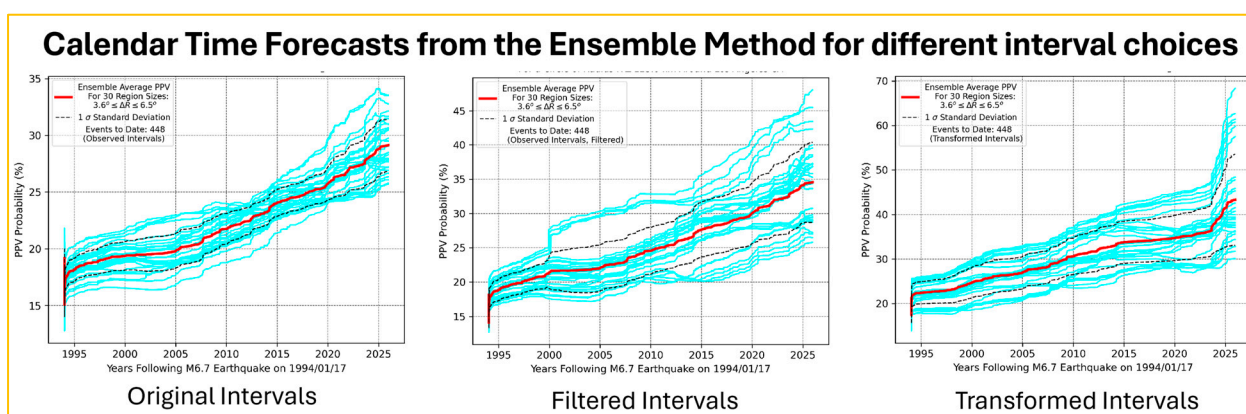


Figure 7. Comparison of PPV for a $M \geq 6.0$ mainshock vs. calendar time forecasts for three choices of intervals: original observed intervals, filtered intervals, and transformed intervals. Presented for a 60-month (5-year) forecast period using an ensemble of 30 regions from 3.6° to 6.5° surrounding Los Angeles, CA. Cyan curves are for the various ensemble members.

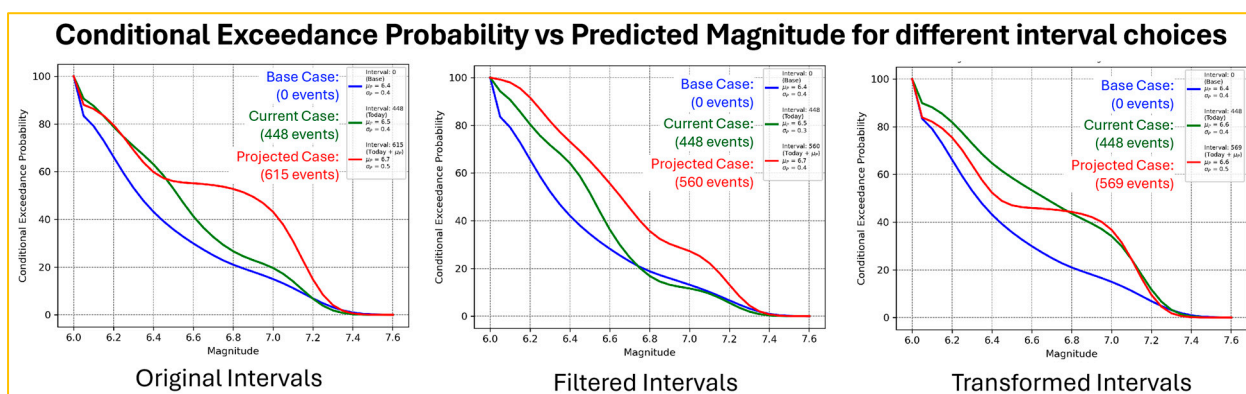


Figure 8. Terminating magnitude exceedance probabilities for three choices of intervals: original observed intervals, filtered intervals, and transformed intervals. Presented for a 60-month (5-year) forecast period using an ensemble of 30 regions from 3.6° to 6.5° surrounding Los Angeles, CA.

Figure 8 shows the corresponding magnitude exceedance curves for the three types of intervals, and Figure 9 shows the same magnitude exceedances for the 25%, 50% (median), and 75% exceedance probabilities as a function of the number of small events that have occurred. Again, the three sets of plots are generally consistent.

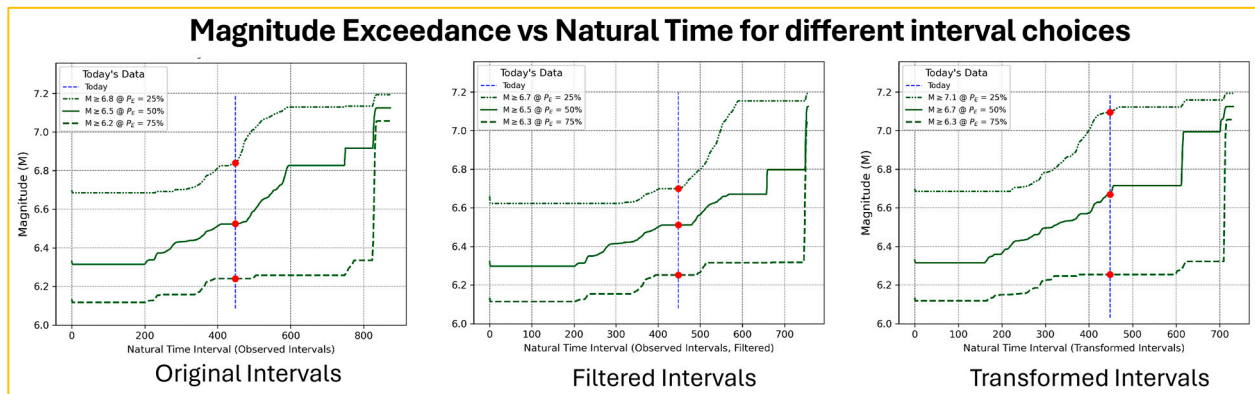


Figure 9. Magnitude exceedance probabilities vs. natural time for original observed intervals, filtered intervals, and transformed intervals for 25%, 50%, and 75% values of exceedance probability. Presented for a 60-month (5-year) forecast period using an ensemble of 30 regions from 3.6° to 6.5° surrounding Los Angeles, CA.

We now compute calendar time exceedance probabilities, the waiting times or lifetimes $\Delta L(t)$, for large earthquake occurrence. To do this, we need to scale the conditional lifetimes since the last large earthquake M_T within each interval $n_{i,j}$. To that end, let the lifetime within an interval $n_{i,j}$ in ensemble i be denoted by $\Delta L(t)_{i,j}$. Then, we scale the lifetimes by the inverse of the factor in Equation (4):

$$\Delta L'(t)_{i,j} = \left(\frac{R_i}{R_C} \right) \Delta L(t)_{i,j} \quad (17)$$

where now $\Delta L'_{i,j}$ is the scaled lifetime since the last large earthquake. We then use the scaled lifetimes to compute the exceedance probabilities.

Figure 10 shows the comparison for the calendar time exceedance probabilities. In all three cases, we show the Poisson probability curve (dashed line) that is based on the average interval between large earthquakes. Similar to Figure 5, we show the curves for several calendar times in the earthquake recurrence cycles. These exceedance curves are for immediately after the last large earthquake at the current time (today); at the current time plus 15 years; and at the current time plus 30 years. Note that a light smoothing has been applied to these curves.

A feature of these calendar time curves is that once the initial large earthquake clustering period has passed, the lifetime until the next large earthquake becomes longer and longer as time passes, until the next large earthquake does eventually occur, as noted in [45–49]. This feature can be inferred by comparing the zero-time curve with the Poisson curve. Initially, the zero-time curve lies below the Poisson curve until a cutoff is reached (shorter waiting times more probable). Subsequently, the zero-time curve lies above the Poisson curve (longer waiting times more probable).

We can then repeat the exceedance curve calculation for natural time (small event counts) using Equation (8) directly, shown in Figure 11. Conditional exceedance curves are shown for several examples of natural times (small event counts): for 0 small events (immediately after the last large earthquake); for 448 small events (the current count in the circular region); and for the current-plus-mean-projected number of small events in the

circular region. The mean projected number is the average number of small events expected until just before the next large earthquake. This mean projected number is computed by finding the mean of all intervals larger than the current number, 448, minus the current number. Note that a light smoothing has been applied to these curves.

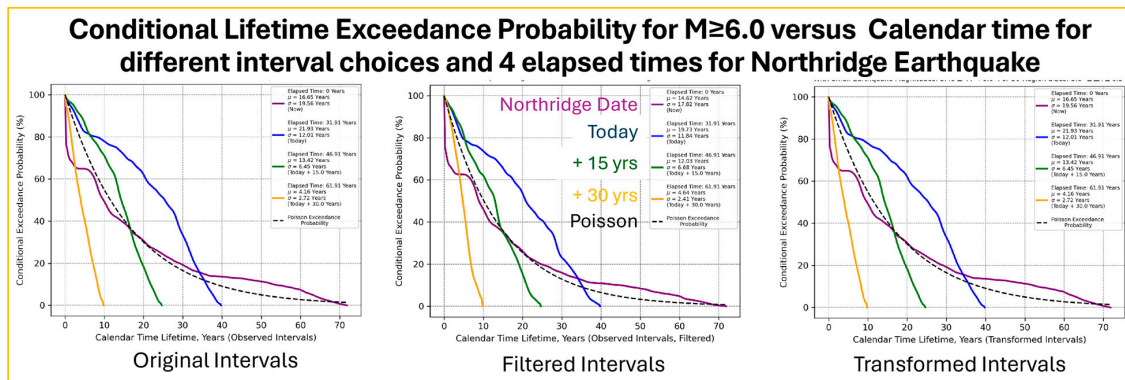


Figure 10. Calendar time exceedance probabilities for original observed intervals, filtered intervals, and transformed intervals. Conditional curves are shown for elapsed times (following the last large earthquake) of 0 years; today, 31.91 years, the current elapsed time following the 1994 Northridge earthquake; today + 15 years from now; and today + 30 years from now. Calculated using an ensemble of 30 regions from 3.6° to 6.5° surrounding Los Angeles, CA.

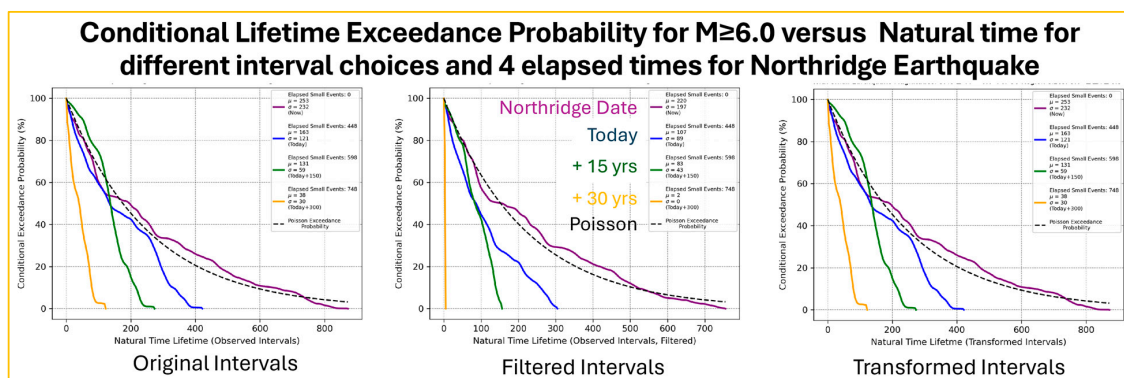


Figure 11. Natural time exceedance probabilities for original observed intervals, filtered intervals, and transformed intervals. Conditional curves are shown for elapsed natural times (following the last large earthquake) of 0 small events; today, 448 small events, the current number following the 1994 Northridge earthquake; today + 150 additional small earthquakes; and today + 300 additional small events. Calculated using an ensemble of 30 regions from 3.6° to 6.5° surrounding Los Angeles, CA.

In this case however, one finds the more intuitively expected result that the longer it has been in natural time since the last large earthquake M_T , the shorter the expected natural time until the next large earthquake. Or stated another way, as the time since the last large earthquake increases, the probability increases for a shorter lifetime, or time to the next large earthquake.

The reason for the different implications of the calendar and natural time curves is the increasing, nonlinear small earthquake quiescence as time passes. This observation has been discussed in [14]. There, it was concluded that the reason for this anomalous slowing down in calendar time (relative to the Poisson curve) is due to an anomalous stiffening/strengthening of the crustal rigidity as the next earthquake approaches due to the closure of small cracks that, when open, weaken the crust. As the rigidity of the crust increases, a transition occurs from sliding via unstable stick slip to sliding via stable slip [6,50], as is well known from many laboratory experiments.

3.2. Validating/Benchmarking the Forecasts

An important consideration is to benchmark the forecasts by comparing them with a recognized, accepted model. This comparison should be viewed as an indicative benchmark of our method's utility rather than a strict validation of equivalence. The UCERF3 model incorporates comprehensive fault geometries and physical parameters, whereas our ensemble method is primarily statistical. The obvious choices are the UCERF2 time-independent forecast and the UCERF3 time-dependent forecast [51,52]. Figure 12 shows the comparison. The UCERF2 forecast for magnitude 6.7, produced in 2007, computed a 30-year forecast of 67% for the Los Angeles box, shown in Figure 12, and a 63% for the San Francisco Bay area for its rectangular box. In 2016, the UCERF3 forecast published the 30-year forecast of 60% for the same Los Angeles box. The UCERF2 30 yr forecast is especially relevant because we are past the midpoint of the 30-year time window. The UCERF3 time-dependent forecast is a valid comparison because it is the official USGS forecast.

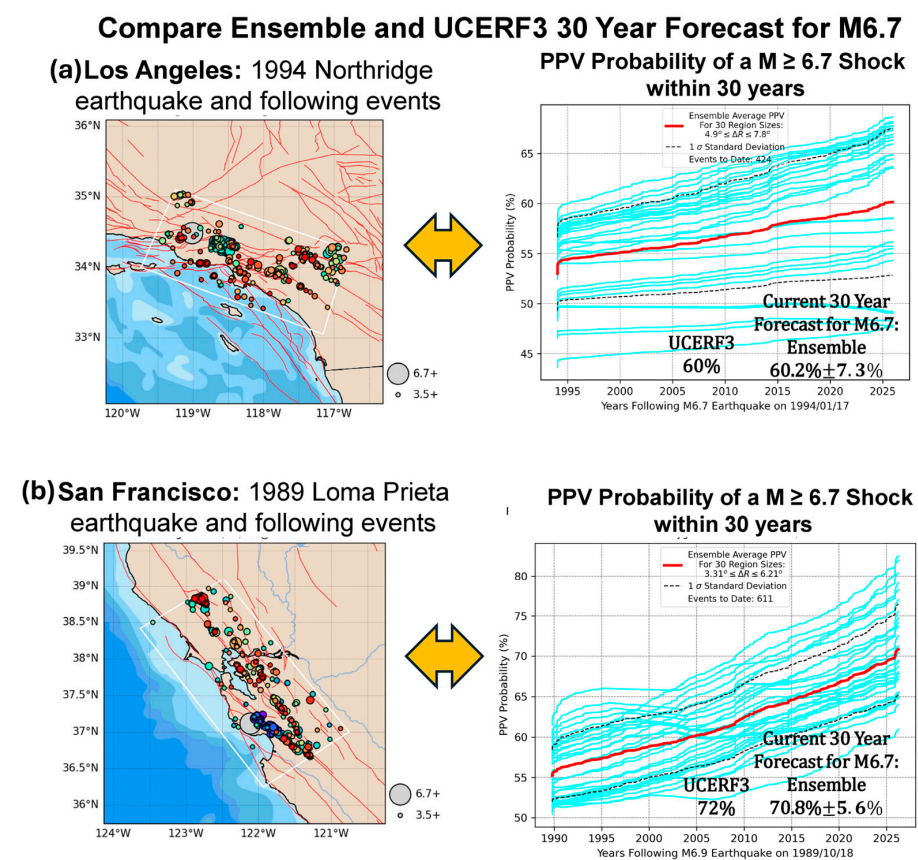


Figure 12. Validation of the ensemble method by comparing with the UCERF3 time-dependent forecast [51] for (a) the Los Angeles and (b) San Francisco boxes defined in the UCERF3 forecast. The forecast curves on the right begin at the time of the 1994 Northridge earthquake for the Los Angeles box and the 1989 Loma Prieta earthquake for the San Francisco box, respectively. The circles on the left figures denote quakes with circle size representing magnitude and color representing the time of the earthquake, with light grey representing the oldest and red representing the newest. The current values of the Los Angeles and San Francisco ensemble 30-year forecasts are listed on the left of the figure, together with the UCERF3 30-year forecasts. Cyan curves are for the various ensemble members.

The UCERF3 forecast was produced in 2014, whereas the ensemble forecast was produced now. But the numbers are similar and within the quoted error bounds for the ensemble method. This similarity provides a useful benchmark for evaluating the quality of the ensemble forecast.

3.3. Forecasts for Other Regions

As a matter of interest, we compute forecasts for a few additional international locations. A caveat is that, since the USGS catalog is not as complete as it is for the United States, the forecasts may not be as reliable as for those in the United States. And since these regions often do not have “official”, “credible” forecasts such as the UCERF3 forecasts, we use instead time-independent conditional Poisson (exponential) forecasts [53,54].

To compute these Poisson forecasts, we need the rate of large earthquakes in the time-scaled ensemble regions. The rate ν_i of ensemble member i is computed from Equation (11) by dividing the number of cycles by the total time-scaled time interval, which is just the sum over all time-scaled time intervals $\tilde{\Delta T}_{i,j}$. We then compute the mean ν_{Ens} and standard deviation σ_{Ens} for the entire ensemble from the set $\{\nu_i\}$ of rates of the individual ensemble members, thus $\nu_{Ens} = \text{mean}(\{\nu_i\})$.

Then, using the mean rate ν_{Ens} , we calculate a conditional time-independent Poisson (exponential) probability $P_{Ens}(\Delta T)$ for the ensemble:

$$P_{Ens}(\Delta T) = 1 - e^{-(\nu_{Ens} \Delta T)} \quad (18)$$

where ΔT is the forecast time. The standard errors $\Delta P_{\pm}(\Delta T)$ of the conditional probability shown in the figures are computed with Equation (18). We use the rates $\nu_{\pm} = (\nu_{Ens} \pm \sigma_{Ens})$ in Equation (18), then compute the difference from $P_{Ens}(\Delta T)$. The results are shown in Figures 13–15 for the international cities Athens, Greece; Chengdu, China; Jakarta, Indonesia; Lima, Peru; Santiago, Chile; and Tangshan, China.

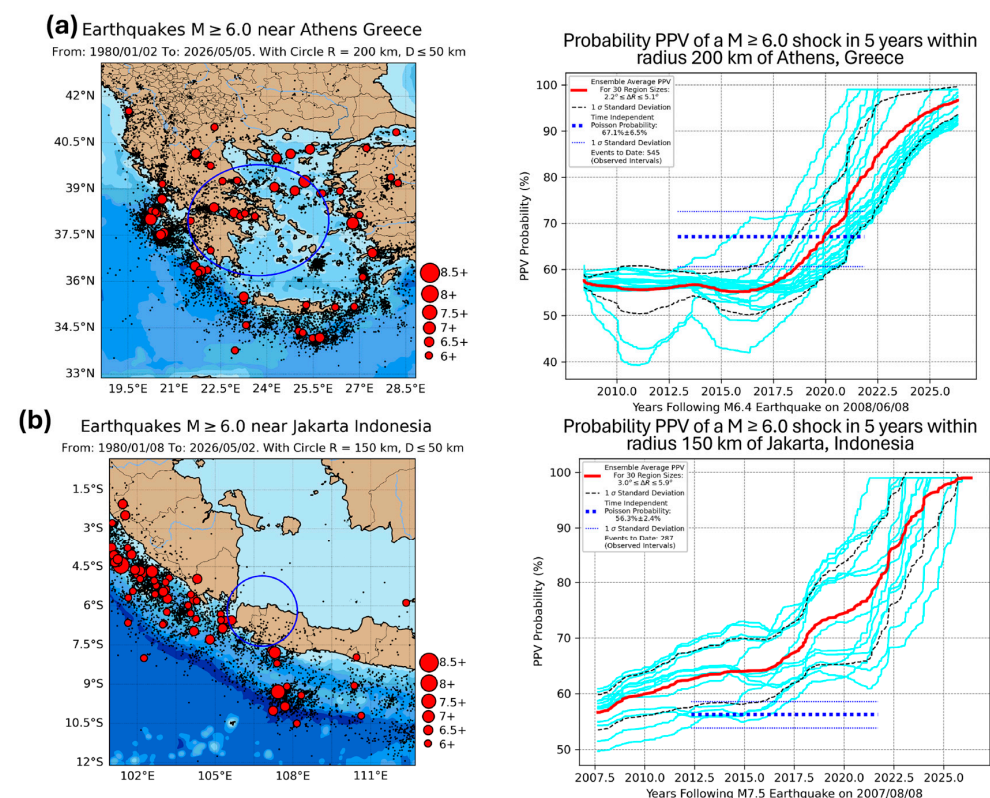


Figure 13. (a) Forecast for magnitude $M \geq 6$ earthquakes within 200 km of Athens, Greece, within 5 years. (b) Forecast for magnitude $M \geq 6$ earthquakes within 150 km of Jakarta, Indonesia, within 5 years. The conditional Poisson (exponential) forecast is also shown as the blue dotted line. The circles on the left figures denote quakes with circle size representing magnitude M , and red being $M \geq 6.0$, and black dots being small earthquakes $4 \leq M \leq 6$. The cyan lines on the right correspond to ensemble results.

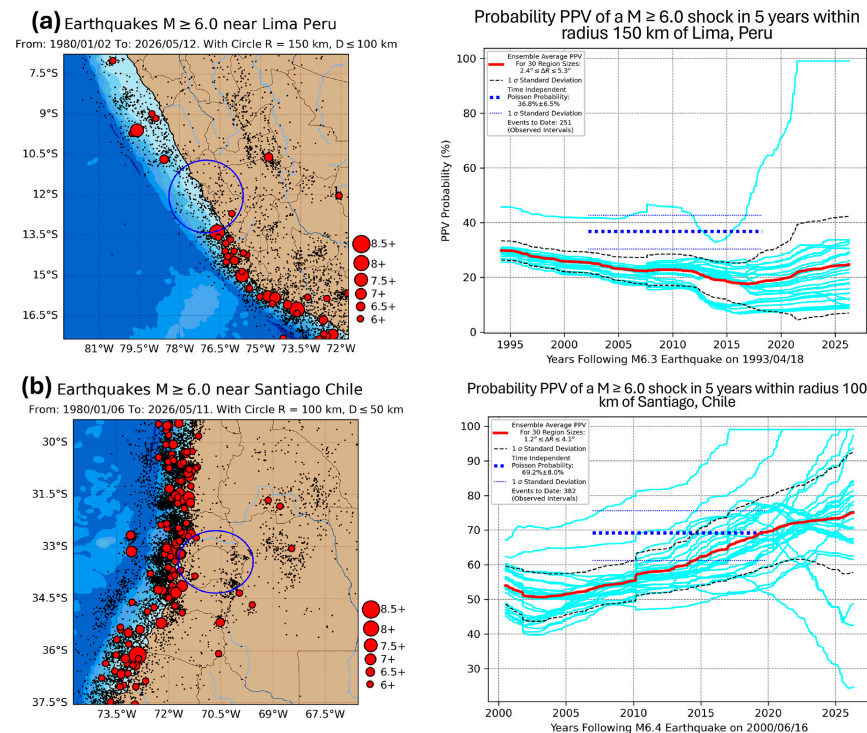


Figure 14. (a) Forecast for magnitude $M \geq 6$ earthquakes within 200 km of Lima, Peru, within 5 years. (b) Forecast for magnitude $M \geq 6$ earthquakes within 100 km of Santiago, Chile, within 5 years. The conditional Poisson (exponential) forecast is also shown as the blue dotted line. The circles on the left figures denote quakes with circle size representing magnitude M , and red being $M \geq 6.0$, and black dots being small earthquakes $4 \leq M \leq 6$. The cyan lines on the right correspond to ensemble results.

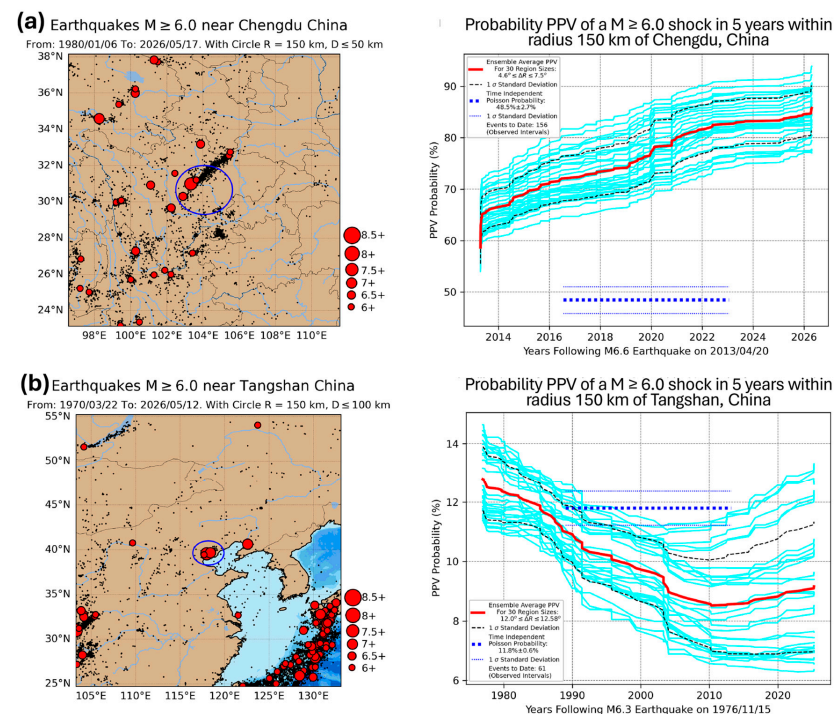


Figure 15. (a) Forecast for magnitude $M \geq 6$ earthquakes within 150 km of Chengdu, China, within 5 years. (b) Forecast for magnitude $M \geq 6$ earthquakes within 150 km of Tangshan, China, within 5 years. The conditional Poisson (exponential) forecast is also shown as the blue dotted line. The circles on the left figures denote quakes with circle size representing magnitude M , and red being $M \geq 6.0$, and black dots being small earthquakes $4 \leq M \leq 6$. The cyan lines on the right correspond to ensemble results.

4. Conclusions

We have developed a new method for earthquake forecasting for arbitrary forecast times and for small geographic regions encompassing multiple earthquake faults. It is generally not as appropriate for individual faults, where quiescence may be the normal mode of behavior. Since the forecasts are conducted in regions, rather than on individual faults, the stability of the Gutenberg–Richter statistics and the associated b -value are observed using least squares fits to the magnitude–frequency curves [55]. The assumption of similar Gutenberg–Richter statistics also amounts to the assumption that we confine analysis to a single tectonic province [55].

Finally, we situate this purely statistical methodology within the broader landscape of modern seismic hazard assessment. While physics-based models that incorporate stress transfer and fault mechanics provide essential insights into seismogenesis, they often rely on physical parameters that are challenging to constrain. Consequently, statistical approaches remain foundational to operational forecasting frameworks [6,56–64]. For example, the UCERF3 model for California integrates Epidemic-Type Aftershock Sequence (ETAS) models [63,65–67], which involve fitting multiple statistical parameters to historical training data. A distinct advantage of the ensemble method presented here is its mathematical parsimony: it requires no empirically tuned free parameters. As such, it provides a straightforward, objective, and complementary tool for rapid probabilistic seismic forecasting. In the current ensemble method, there are no free parameters that must be set using data. This contrasts with the UCERF3 forecast, which is the accepted official forecast for the state of California, and lists at least 15 major assumptions which, in some cases, may be difficult to justify. In addition, the UCERF3 model has many parameters whose values must be estimated. And in particular, the UCERF3 catalog has a component that uses the ETAS model to compute the forecast [63,65–67].

We conclude that the ensemble method is an appropriate and useful method for when a forecast for small geographic regions is desired on a frequent basis. It can be carried out rapidly and easily on a laptop computer in a few minutes of computation. For that reason, the ensemble method constitutes a convenient and potentially powerful addition to present earthquake forecast methods.

Author Contributions: Conceptualization, J.B.R., I.B., A.D., L.G.L., G.F. and K.N.; methodology, J.B.R. and K.N.; software, J.B.R. and K.N.; validation, J.B.R., I.B. and K.N.; formal analysis, J.B.R.; investigation, J.B.R.; resources, J.B.R. and I.B.; data curation, J.B.R.; writing—original draft preparation, J.B.R.; writing—review and editing, A.D., L.G.L., G.F. and K.N.; visualization, J.B.R.; supervision, J.B.R.; project administration, J.B.R.; funding acquisition, J.B.R. All authors have read and agreed to the published version of the manuscript.

Funding: Funding for this project has been provided by a generous gift from Dr. John LaBrecque to the University of California, Davis.

Data Availability Statement: The data presented in this study are available in the USGS ComCat catalog at <https://earthquake.usgs.gov/earthquakes/search/>, accessed on 16 June 2026, reference number [67]. An included method in the Python 3.12 code mentioned above can be used to download these data for analysis. Python code that can be used to reproduce the results of this paper can be found at the Zenodo site: <https://doi.org/10.5281/zenodo.19390594>, accessed on 16 June 2026.

Acknowledgments: The authors would also like to acknowledge an informative conversation with Jeanne Hardebeck of the USGS.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Rundle, J.B.; Baughmann, I.; Donnellan, A.; Ludwig, L.G.; Fox, G.C.; Nanjo, K. Calendar Time Local Earthquake Forecasts from Earthquake Nowcasts: A Do-It-Yourself (DIY) Ensemble Method. *arXiv* **2025**, arXiv:2512.06572. [\[CrossRef\]](#)
2. Rundle, J.B.; Baughman, I.; Donnellan, A.; Grant Ludwig, L.; Fox, G.C. From local earthquake nowcasting to natural time forecasting: A simple do-it-yourself (DIY) method. *Earth Space Sci.* **2026**, *13*, e2025EA004820. [\[CrossRef\]](#)
3. Varotsos, P.; Sarlis, N.V.; Skordas, E.S. Spatiotemporal complexity aspects on the interrelation between Seismic Electric Signals and seismicity. *Pract. Athens Acad.* **2001**, *76*, 294–321.
4. Varotsos, P.; Sarlis, N.V.; Skordas, E.S. *Natural Time Analysis: The New View of Time. Precursory Seismic Electric Signals, Earthquakes and Other Complex Time-Series*; Springer: Berlin/Heidelberg, Germany, 2011. [\[CrossRef\]](#)
5. Varotsos, P.; Sarlis, N.V.; Skordas, E.S. Study of the temporal correlations in the magnitude time series before major earthquakes in Japan. *J. Geophys. Res. Space Phys.* **2014**, *119*, 9192–9206. [\[CrossRef\]](#)
6. Holliday, J.R.; Rundle, J.B.; Turcotte, D.L.; Klein, W.; Tiampo, K.F. Space-time clustering and correlations of major earthquakes. *Phys. Rev. Lett.* **2006**, *97*, 238501. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Rundle, J.B.; Donnellan, A.; Grant Ludwig, L.; Gong, G.; Turcotte, D.L.; Luginbuhl, M. Nowcasting earthquakes. *Earth Space Sci.* **2016**, *3*, 480–486. [\[CrossRef\]](#)
8. Rundle, J.B.; Stein, S.; Donnellan, A.; Turcotte, D.L.; Klein, W.; Saylor, C. The complex dynamics of earthquake fault systems: New approaches to forecasting and nowcasting of earthquakes. *Rep. Prog. Phys.* **2021**, *84*, 076801. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Rundle, J.B.; Luginbuhl, M.; Giguere, A.; Turcotte, D.L. Natural time, nowcasting and the physics of earthquakes: Estimation of risk to global megacities. *Pure Appl. Geophys.* **2018**, *175*, 647–660. [\[CrossRef\]](#)
10. Rundle, J.B.; Luginbuhl, M.; Polina, K.; Turcotte, D.L.; Donnellan, A.; Grayson, M. Nowcasting Great Global Earthquake and Tsunami Sources. *Pure Appl. Geophys.* **2020**, *177*, 359–368. [\[CrossRef\]](#)
11. Rundle, J.B.; Giguere, A.; Turcotte, D.L.; Crutchfield, J.P.; Donnellan, A. Global seismic nowcasting with Shannon information entropy. *Earth Space Sci.* **2019**, *6*, 456–472. [\[CrossRef\]](#) [\[PubMed\]](#)
12. Rundle, J.B.; Donnellan, A. Nowcasting earthquakes in Southern California with machine learning: Bursts, swarms, and aftershocks may be related to levels of regional tectonic stress. *Earth Space Sci.* **2020**, *7*, e2020EA0010. [\[CrossRef\]](#)
13. Rundle, J.B.; Donnellan, A.; Fox, G.; Crutchfield, J.P.; Granat, R. Nowcasting earthquakes: Imaging the earthquake cycle in California with machine learning. *Earth Space Sci.* **2021**, *8*, e2021EA001757. [\[CrossRef\]](#)
14. Rundle, J.B.; Yazbeck, J.; Donnellan, A.; Fox, G.; Ludwig, L.G.; Heflin, M.; Crutchfield, J. Optimizing earthquake nowcasting with machine learning: The role of strain hardening in the earthquake cycle. *Earth Space Sci.* **2022**, *9*, e2022EA002343. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Rundle, J.B.; Donnellan, A.; Fox, G.; Crutchfield, J.P. Nowcasting earthquakes by visualizing the earthquake cycle with machine learning: A comparison of two methods. *Surv. Geophys.* **2022**, *43*, 483–501. [\[CrossRef\]](#)
16. Rundle, J.B.; Baughman, I.; Zhang, T. Nowcasting earthquakes with stochastic simulations: Information entropy of earthquake catalogs. *Earth Space Sci.* **2024**, *11*, e2023EA003367. [\[CrossRef\]](#)
17. Fox, G.C.; Rundle, J.B.; Donnellan, A.; Feng, B. Earthquake nowcasting with deep learning. *Geohazards* **2022**, *3*, 199–226. [\[CrossRef\]](#)
18. Jafari, A.; Fox, G.; Rundle, J.B.; Donnellan, A.; Ludwig, L.G. Time series foundation models and deep learning architectures for earthquake temporal and spatial nowcasting. *GeoHazards* **2024**, *5*, 1247–1274. [\[CrossRef\]](#)
19. Pasari, S.; Mehta, A. Nowcasting earthquakes in the northwest Himalaya and surrounding regions. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.* **2018**, *XLII-5*, 855–859. [\[CrossRef\]](#)
20. Pasari, S.; Sharma, Y. Contemporary earthquake hazards in the West-northwest Himalaya: A statistical perspective through natural times. *Bull. Seismol. Soc. Am.* **2020**, *91*, 3358–3369. [\[CrossRef\]](#)
21. Pasari, S. Nowcasting earthquakes in the Bay-of-Bengal region. *Pure Appl. Geophys.* **2019**, *23*, 537–559. [\[CrossRef\]](#)
22. Pasari, S. Stochastic Modeling of Earthquake Interevent Counts (Natural Times) in Northwest Himalaya and Adjoining Regions. In *Mathematical Modeling and Computational Tools*; Bhattacharyya, S., Kumar, J., Ghoshal, K., Eds.; Springer Proceedings in Mathematics & Statistics; Springer: Singapore, 2020; Volume 320, pp. 495–501. [\[CrossRef\]](#)
23. Pasari, S.; Simanjuntak, A.V.; Neha Sharma, Y. Nowcasting earthquakes in Sulawesi island, Indonesia. *Geosci. Lett.* **2021**, *8*, 27. [\[CrossRef\]](#)
24. Pasari, S. Nowcasting earthquakes in Iran: A quantitative analysis of earthquake hazards through natural times. *J. Afr. Earth Sci.* **2023**, *198*, 104821. [\[CrossRef\]](#)
25. Devi, S.; Pasari, S. Nowcasting earthquakes in the Philippines archipelago. *J. Seismol.* **2025**, *29*, 505–524. [\[CrossRef\]](#)
26. Devi, S.; Pasari, S. Earthquake cycle progression in major city regions of Taiwan through nowcasting technique. *J. Seismol.* **2025**, *29*, 603–623. [\[CrossRef\]](#)
27. Pasari, S. Neha Nowcasting-based earthquake hazard estimation at major cities in New Zealand. *Pure Appl. Geophys.* **2022**, *179*, 1597–1612. [\[CrossRef\]](#)

28. Pasari, S.; Sharma, Y. Quantifying the current state of earthquake hazards in Nepal. *Appl. Comput. Geosci.* **2021**, *10*, 100058. [\[CrossRef\]](#)
29. Pasari, S.; Simanjuntak, A.V.; Mehta, A.; Neha Sharma, Y. The current state of earthquake potential on Java Island, Indonesia. *Pure Appl. Geophys.* **2021**, *178*, 2789–2806. [\[CrossRef\]](#)
30. Devi, S.; Pasari, S.; Mehta, A. Seismic cycle progression in major cities of Myanmar using earthquake nowcasting. *J. Seismol.* **2025**, *29*, 1691–1707. [\[CrossRef\]](#)
31. Zhang, S.; Zhang, Y. Application of Nowcasting Method to Assess Significant Earthquake Potential in North China. In *Exploring the Unseen Hazards of Our World*; IntechOpen: London, UK, 2024. [\[CrossRef\]](#)
32. Devi, S.; Pasari, S. Earthquake Hazard Evaluation in Peninsular India with Nowcasting Approach. In *2025 IEEE International Conference on Next-Gen Technologies of Artificial Intelligence and Geoscience Remote Sensing (EarthSense)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–5. [\[CrossRef\]](#)
33. Pasari, S.; Simanjuntak, A.V.; Mehta, A.; Neha Sharma, Y. A synoptic view of the natural time distribution and contemporary earthquake hazards in Sumatra, Indonesia. *Nat. Hazards* **2021**, *108*, 309–321. [\[CrossRef\]](#)
34. Bhatia, A.; Pasari, S.; Mehta, A. Earthquake forecasting using artificial neural networks. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2018**, *42*, 823–827. [\[CrossRef\]](#)
35. Luginbuhl, M.; Rundle, J.B.; Turcotte, D.L. Natural time and earthquake nowcasting. *Earth Space Sci.* **2018**, *5*, 225–231. [\[CrossRef\]](#)
36. Shafiee, A.H.; Mesgar Asl, H.; Samani, B. Determination of earthquake potential score for the western margin of the Lut Block, Iran, using the nowcasting method. *J. Seismol.* **2025**, *29*, 1793–1807. [\[CrossRef\]](#)
37. Chouliaras, G. Seismicity anomalies prior to 8 June 2008, Mw=6.4 earthquake in Western Greece. *Nat. Hazards Earth Syst. Sci.* **2009**, *9*, 327–335. [\[CrossRef\]](#)
38. Chouliaras, G.; Skordas, E.S.; Sarlis, N.V. Earthquake nowcasting: Retrospective testing in Greece. *Entropy* **2023**, *25*, 379. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Perez-Oregon, J.; Angulo-Brown, F.; Sarlis, N.V. Nowcasting Avalanches as Earthquakes and the Predictability of Strong Avalanches in the Olami-Feder-Christensen Model. *Entropy* **2020**, *22*, 1228. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Manyele, A.; Mwambela, A. Simulated PGA Shaking Maps for the Magnitude 6.8 Lake Tanganyika earthquake of December 5, 2005 and the observed damages across South Western Tanzania. *Int. J. Sci. Res. Publ.* **2014**, *4*, 1–5.
41. Minson, S.E.; Baltay, A.S.; Cochran, E.S.; McBride, S.K.; Milner, K.R. Shaking is almost always a surprise: The earthquakes that produce significant ground motion. *Bull. Seismol. Soc. Am.* **2021**, *92*, 460–468. [\[CrossRef\]](#)
42. Mandrekar, J.N. Receiver operating characteristic curve in diagnostic test assessment. *J. Thorac. Oncol.* **2010**, *5*, 1315–1316. [\[CrossRef\]](#) [\[PubMed\]](#)
43. Powers David, M.W. Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness & Correlation. *J. Mach. Learn. Technol.* **2011**, *2*, 37–63. [\[CrossRef\]](#)
44. Gardner, J.K.; Knopoff, L. Is the sequence of earthquakes in Southern California, with aftershocks removed, Poissonian? *Bull. Seismol. Soc. Am.* **1974**, *64*, 1363–1367. [\[CrossRef\]](#)
45. Davis, P.M.; Jackson, D.D.; Kagan, Y.Y. The longer it has been since the last earthquake, the longer the expected time till the next? *Bull. Seismol. Soc. Am.* **1989**, *79*, 1439–1456. [\[CrossRef\]](#)
46. Sornette, D.; Knopoff, L. The paradox of the expected time until the next earthquake. *Bull. Seismol. Soc. Am.* **1997**, *87*, 789–798. [\[CrossRef\]](#)
47. Corral, Á. Time-decreasing hazard and increasing time until the next earthquake. *Phys. Rev. E—Stat. Nonlinear Soft Matter Phys.* **2005**, *71*, 017101. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Jonsdottir, K.; Lindman, M.; Roberts, R.; Lund, B.; Bödvarsson, R. Modelling fundamental waiting time distributions for earthquake sequences. *Tectonophysics* **2006**, *424*, 195–208. [\[CrossRef\]](#)
49. Guglielmi, A.V.; Zotov, O.D. About the waiting time for a strong earthquake. *arXiv* **2022**, arXiv:2209.00176. [\[CrossRef\]](#)
50. Dieterich, J.H. Modeling of rock friction: 1. Experimental results and constitutive equations. *J. Geophys. Res. Solid Earth* **1979**, *84*, 2161–2168. [\[CrossRef\]](#)
51. Field, E.H.; Arrowsmith, R.J.; Biasi, G.P.; Bird, P.; Dawson, T.E.; Felzer, K.R.; Jackson, D.D.; Johnson, K.M.; Jordan, T.H.; Madden, C.; et al. Uniform California earthquake rupture forecast, version 3 (UCERF3)—The time-independent model. *Bull. Seismol. Soc. Am.* **2014**, *104*, 1122–1180. [\[CrossRef\]](#)
52. Field, E.H.; Dawson, T.E.; Felzer, K.R.; Frankel, A.D.; Gupta, V.; Jordan, T.H.; Parsons, T.; Petersen, M.D.; Stein, R.S.; Weldon, R.J.; et al. Uniform California earthquake rupture forecast, version 2 (UCERF 2). *Bull. Seismol. Soc. Am.* **2009**, *99*, 2053–2107. [\[CrossRef\]](#)
53. Daley, D.J.; Vere-Jones, D. *An Introduction to the Theory of Point Processes*; Springer Series in Statistics; Springer: New York, NY, USA, 1998. [\[CrossRef\]](#)
54. Holliday, J.R.; Turcotte, D.L.; Rundle, J.B. A review of earthquake statistics: Fault and seismicity-based models, ETAS and BASS. *Earth Sci. Math.* **1998**, *1*, 1003–1024. [\[CrossRef\]](#)

55. Schorlemmer, D.; Wiemer, S.; Wyss, M. Variations in earthquake-size distribution across different stress regimes. *Nature* **2005**, *437*, 539–542. [[CrossRef](#)] [[PubMed](#)]
56. Ogata, Y. Statistics of earthquake activity: Models and methods for earthquake predictability studies. *Annu. Rev. Earth Planet. Sci.* **2017**, *45*, 497–527. [[CrossRef](#)]
57. Iacopetti, S.; Cremen, G.; Galasso, C. Validation of the epidemic-type aftershock sequence (ETAS) models for simulation-based seismic hazard assessments. *Seismol. Soc. Am.* **2022**, *93*, 1601–1618. [[CrossRef](#)]
58. Console, R. Short-term and long-term earthquake occurrence models for Italy: ETES, ERS and LTST. *Ann. Geophys.* **2010**, *53*, 3. [[CrossRef](#)]
59. Helmstetter, A.; Sornette, D. Importance of direct and indirect triggered seismicity in the ETAS model of seismicity. *Geophys. Res. Lett.* **2003**, *30*, 1576. [[CrossRef](#)]
60. Ogata, Y.; Zhuang, J. Space-time ETAS models and an improved extension. *Tectonophysics* **2006**, *413*, 13–23. [[CrossRef](#)]
61. Zhuang, J. Next-day earthquake forecasts for the Japan region generated by the ETAS model. *Earth Planets Space* **2011**, *63*, 207–216. [[CrossRef](#)]
62. Field, E.H.; Milner, K.R.; Hardebeck, J.L.; Page, M.T.; van der Elst, N.; Jordan, T.H.; Michael, A.J.; Shaw, B.E.; Werner, M.J. A spatiotemporal clustering model for the third Uniform California Earthquake Rupture Forecast (UCERF3-ETAS): Toward an operational earthquake forecast. *Bull. Seismol. Soc. Am.* **2017**, *107*, 1049–1081. [[CrossRef](#)]
63. Ogata, Y. Significant improvements of the space-time ETAS model for forecasting of accurate baseline seismicity. *Earth Planets Space* **2011**, *63*, 217–229. [[CrossRef](#)]
64. Savran, W.H.; Werner, M.J.; Marzocchi, W.; Rhoades, D.A.; Jackson, D.D.; Milner, K.; Field, E.; Michael, A. Pseudoprospective evaluation of UCERF3-ETAS forecasts during the 2019 Ridgecrest sequence. *Bull. Seismol. Soc. Am.* **2020**, *110*, 1799–1817. [[CrossRef](#)]
65. Field, E.H.; Milner, K.R.; Page, M.T.; Savran, W.H.; van der Elst, N. Improvements to the third uniform California earthquake rupture forecast ETAS model (UCERF3-ETAS). *Seism. Rec.* **2021**, *1*, 117–125. [[CrossRef](#)]
66. Milner, K.R.; Field, E.H.; Savran, W.H.; Page, M.T.; Jordan, T.H. Operational earthquake forecasting during the 2019 Ridgecrest, California, earthquake sequence with the UCERF3-ETAS model. *Seismol. Res. Lett.* **2020**, *91*, 1567–1578. [[CrossRef](#)]
67. USGS Earthquake Catalog. Available online: <https://earthquake.usgs.gov/earthquakes/search/> (accessed on 16 June 2026).

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.