USING EPICENTER LOCATION TO DIFFERENTIATE EVENTS FROM NATURAL BACKGROUND SEISMICITY

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ABSTRACT
Efforts to more effectively monitor the Comprehensive Nuclear-Test-Ban Treaty (commonly referred to as the CTBT) include research into methods of seismic discrimination. The most common seismic discriminants exploit differences in seismic amplitude for differing source types. Amplitude discriminants are quite effective when wave-propagation (a.k.a. path) effects are properly accounted for. However, because path effects can be exceedingly complex, path calibration is often accomplished empirically by spatially interpolating amplitude characteristics for a set of calibration earthquakes with techniques like Bayesian kriging (Schultz et al., 1998). As a result, amplitude discriminants can be highly effective when natural seismicity provides sufficient event coverage to characterize a region. However, amplitude discrimination can become less effective for events that are far from historical (path-calibration) events. It is intuitive that events occurring at a distance from historical seismicity patterns are inherently suspect. However, quantifying the degree to which a particular event is unexpected could be of great utility in CTBT monitoring. Epicenter location is commonly used as a qualitative discriminant. For instance, if a seismic event is located in the deep ocean, then the event is generally considered to be an earthquake. Such qualitative uses of seismic location have great utility; however, a quantitative method to differentiate events from the natural pattern of seismicity could significantly advance the applicability of location as a discriminant for source type. Clustering of earthquake epicenters is the underlying aspect of earthquake seismicity that allows for an epicenter-based discriminant, and we explore the use of fractal characterization of clustering to characterize seismicity patterns. This fractal relationship can be combined with the Gutenburg-Richter relationship to form a complete seismicity model as a function of magnitude and distance from any point. Such a model can then be fit to seismicity catalogues and extrapolated down to the small magnitudes of concern to CTBT monitoring, where global catalogues are often incomplete. By characterizing the magnitude-spatial distribution of earthquakes, we can evaluate the likelihood that an event at any given location and magnitude is drawn from the background population. The use of this technique can help to identifying events that are inconsistent with historic seismicity, complementing more conventional methods that are applicable in situations where seismic amplitudes from nearby events can be directly compared.

Key Words: Location, Seismic Regionalization, Calibration, Crustal Structure.
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OBJECTIVE

This study aims to better quantify the use of seismic location to assess source type. Qualitative assessments of seismic source type derived from source location can be useful; however, these qualitative guidelines are generally applied to situations where the physical conditions at the source preclude underground nuclear testing procedures (e.g. under thousands of meters of water). There is considerable utility in further developing seismic location as a more general indicator of source type, and we propose a location-based method that examines the probability that an event was drawn from the magnitude-location population of earthquakes. We characterize the magnitude-location population using a fractal model of spatial clustering in concert with the Gutenburg-Richter magnitude distribution. Using this fractal model, events occurring far from natural seismicity, where amplitude discriminants are less well calibrated, can be identified as outliers to the background population of earthquakes. Of course this technique does not discriminate between the various types of man-made explosions, but the ability to assess the fit of an event into the natural pattern of seismicity can be useful for monitoring. This study focuses on source identification applications of the proposed fractal method; however, we find that this technique has a wide range of possible applications. For example it may provide a better spatially varying map of the expected seismicity rate for small events than a typical b-value extrapolation. Other possible applications are given brief mention below.

RESEARCH ACCOMPLISHED

Parameterization of the magnitude-location distribution

The joint magnitude-spatial distribution of earthquakes is difficult to assess across a broad magnitude range, due to limitations of seismicity catalogues. Low magnitude events are often under represented, due to network detection limitations, and large magnitude events are poorly sampled, due to long recurrence intervals and the short time span covered by catalogues. Likewise, the spatial distribution of earthquakes in low seismicity regions is often poorly characterized, due to the same seismicity catalogue limitations. It is common practice to parameterize the magnitude distribution of earthquakes using the Gutenburg-Richter relationship (Gutenburg and Richter, 1944):

$$\log(N) = a - bM \qquad [1]$$

N is the number of events; M is the magnitude; *a* and *b* are constants. Parameterization enables the magnitude distribution to be estimated beyond the empirically characterized segment of the distribution. Therefore, parameterization is used (albeit with great caution) to estimate both the recurrence time of large earthquakes and the large number of small events that are undetected. Like the magnitude distribution, the spatial distribution can be parameterized. The spatial distribution of earthquakes is well characterized by fractal-clustering models (e.g. Henderson et al., 1994; Oncel et al., 1996).

There are a number of fractal models that can be used to characterize the clustering of earthquake epicenters, but use of the "correlation dimension" (equations [2] and [3]) is particularly robust due to the cumulative nature of the methodology. The fractal correlation function (as outlined in Henderson et al., 1994) is defined as:

$$C_p(r) = \sum_{i=1}^{K} H(r - \|x_p - x_i\|) \qquad [2]$$

where K is the number of points (events in the seismicity catalogue); r is the radial distance under consideration; H is the Heavyside function that is 0 when the arguments evaluate to less then 0, and H is 1 otherwise; the variable *x* holds the location of each event in the seismicity catalogue, with *xp* representing the point at which the correlation function is evaluated. The double bars represent the scalar distance between points. Equation [2] is just the number of events in the catalogue within a distance *r* from the point *p*. Making use of the correlation function, we use a fractal model of the following form to characterize the spatial distribution of epicenters:

$$\log(C(r)) = c + D\log(r) \qquad [3]$$

where *c* and *D* are constants. *D* is commonly referred to as the fractal dimension of the data set, which is simply the linear slope of [3] in log space. In the case of earthquake clustering analysis, the constant *c* determines the overall rate of seismicity. Figure 1 shows the fractal relationship of epicenters relative to three locations with distinctly different seismicity rates. The fractal model is seen to be a good parameterization of the spatial distribution in all three instances, but the fractal dimension and rate of seismicity are seen to be dependent on the point under consideration (i.e. fractal characterization of seismicity is spatially non-stationary).

We use the fractal model of equation [3] in concert with the Gutenburg-Richter (G-R) relationship [1] to characterize the joint magnitude-spatial distribution. Both the magnitude and spatial distributions are log-linear relationships for the expected number of events at specific magnitudes and locations, respectively, and we use this commonality to join the two distributions into the following relationship:

$$\log(N) = A + bM + D\log(r) \qquad [4]$$

where *A* is a new constant and the other variables are defined above. Equation [4] describes a plane that can be used to model the expected number of earthquakes with magnitude *M* within a distance *r* from a given location. We note that the Gutenburg-Richter relationship has been shown to be a fractal relationship (Turcotte, 1989), making [4] a double fractal.

Figure 2 shows the joint magnitude-spatial distribution at the same three points that are shown in Figure 1.

Figure 1 illustrates that the slope of each plane in the spatial dimension is distinctly different. The slope in the magnitude direction is more stationary with a value of about one. Figure 2 shows that the expected number of events at a given magnitude and distance from each point can be estimated by using the joint magnitude-spatial fractal characterization, and this provides a means to assess the surprise associated with the occurrence of an event with a given magnitude and location. We present some examples of CTBT application of this technique below, and we now focus on the fit of the joint fractal distribution and its predictive capabilities.

Data fit and predictability of the joint fractal distribution

In this study we make use of the relocated ISC catalogue presented in Engdahl et al. (1998). This catalogue provides good data coverage for globally located events from 1964 through to the present; however, we make use of the 1964-1996 portion of the catalogue in this study. The inclusion of other catalogues, particularly catalogues that are complete to lower magnitude, will be important in the future development and testing of the joint fractal parameterization.

The planar fractal model fits the magnitude-spatial distribution of earthquakes well. For the example locations shown in Figure 2 the correlation coefficients between the fractal models and the catalogue data range between 0.78 and 0.88. The high degree of correlation agrees with the qualitative assessment of the planar nature of the empirical magnitude-spatial distribution. We also found that higher-order terms are statistically significant in fitting the data; however, the correlation coefficients were only marginally improved when higher-order terms were included. Detailed analysis of the empirical data leads us to believe that the curvature of the surfaces has to do with the preferential binning of events into integer number magnitudes, which causes a periodic peak at integer-valued magnitudes (Figure 2).

By parameterizing the joint magnitude-spatial distribution at regularly spaced points that cover a region, the expected number of events in that region can be calculated by summation. The expected number of events in a region is commonly calculated by arbitrarily bounding the region and characterizing the magnitude distribution therein with the Gutenberg-Richter relationship. This method assumes that the rates of seismicity within the region are stationary, and this assumption is commonly violated. Alternatively, a fractal model can be developed on a grid of points within the region, and the expected number of earthquakes at each point can be summed to provide an estimate of the expected number of events in the region. The grid spacing can be adjusted to suite the degree of non-stationarity in the region. Figure 3 shows a map of the expected number of earthquakes within 2° of grid points in a portion of the Middle East. The widely varying values on the map demonstrate the highly non-stationary seismicity rates (see figure caption). Using this map we can sum the contribution of each point to estimate the seismicity rate in the whole region. Figure 4a shows that summing the fractal-model predictions at each point agrees with the seismicity rate in the region. Therefore, decomposing the seismicity catalogue into point-specific fractal representations and summing the fractal models reproduces the seismicity rate. This is a circular test of the method, but it does demonstrate the validity of representing seismicity with fractal models. A more rigorous test is shown in Figure 4b, where the fractal summation method is used to predict the seismicity rates for a period of time following the catalogue that was used to construct the fractal models. The expected number of events in Figure 4b is in good agreement with observed seismicity rates, demonstrating the predictive capability of the fractal technique.

The example in Figure 4b suggests that the seismicity rate is temporally stationary in a large region. However, temporal stationarity may not hold in local areas where an aftershock sequence, for example, could temporarily boost the seismicity rate. Temporal clustering of earthquakes has also been characterized with fractal models (e.g. Smalley et al., 1987), and this temporal dependence should be accounted for when the study area is local in scale.

The ability to estimate the magnitude distribution within an arbitrary region is of fundamental utility in seismology. Well-defined portions of the seismicity catalogue can be used to constrain the parameters of the fractal model, and predictions can then be made for the number of potentially damaging (large) earthquakes.

Quantifying the expected number of earthquakes of a given magnitude is at the core of earthquake hazard analysis, and we are applying the fractal method to these problems. While hazard studies focus on large earthquakes, seismic monitoring focuses on the other end of the magnitude distribution, which can be just as poorly sampled. Some of the monitoring applications of this technique are: 1) estimating the event-occurrence rate in a specific area as a function of monitoring threshold, 2) identification of mine blasts by their non-fractal magnitude distribution, and 3) assessing the surprise associated with the occurrence of an event with a certain magnitude and location. We devote the remainder of this discussion to the third application mentioned.

Fractal characterization as a location disciminant

How much of a surprise is the occurrence of an event with some magnitude and location? This question is at the heart of using location to identifiy source type, and fractal parameterization can help to quantify this level of surprise. Figure 4 shows the expected number of events at the location of three known nuclear tests verses the number of expected events in a 30 year time period at the locations of similar-sized events in the global catalogue. The bar graphs show the distribution of expected numbers of events at locations where global-catalogue events actually occurred. This gives an empirical distribution of the background pattern of seismicity. The number of expected events (also for a 30 year time period) at the location of the nuclear test is calculated and compared to the global distribution.

Fractal characterization of the global distribution of earthquakes indicates that, taken together, the magnitude and location of the three nuclear tests is uncommon. In other words, the occurrence of these events is surprising. In the case of the 1964 French test (North Africa), the event is seen to be exceedingly unusual.

Based on the location-outlier analysis this event is quite suspicious and would warrant further investigation. The 1998 Indian and Pakistani tests are also outliers, but they are not as unusual as the French test. This is not surprising, considering that the Pakistani test is in a zone of increased seismicity and the Indian test is relatively nearby. Nonetheless, even the Pakistani test, which is in an active tectonic region, is an outlier to the global population of earthquakes, demonstrating the applicability of the fractal methodology. We used the entire ISC catalogue for these tests of the fractal method, and the ISC reports all seismic events including other nuclear explosions. We are currently working to cull non-earthquake events from the ISC catalogue, which is likely to put the example explosions shown in Figure 5 further out on the tails of the distribution.

The examples presented above suggest that using location and magnitude together to identify non-earthquake seismic event is promising. However, more testing of this method is warranted. Of particular interest is the performance of this technique at lower magnitudes. At lower magnitudes the expected number of earthquakes grows exponentially, and there is some threshold below which an event of a given magnitude is not surprising anywhere on the globe.

CONCLUSIONS AND RECOMMENDATIONS

The joint distribution of earthquake magnitude and location can be characterized with a double fractal model (Equation 4; Figure 2). The examples presented above demonstrate that a seismicity catalogue can be decomposed into point-specific fractal models (figures 2 and 3), and that summing the expected number of events at regularly spaced points agrees with the starting seismicity rates in the region (Figure 4a). In a more rigorous test, summing the expected number of events at each point agrees with the seismicity rate for a subsequent portion of the catalogue that was not used to construct the fractal models (Figure 4b).

Fractal characterization of the joint magnitude-spatial distribution of earthquakes provides a promising means to identify non-earthquake sources. We demonstrate the degree to which three nuclear tests are outliers to the global magnitude-location distribution of earthquakes (Figure 5). An explosion in North Africa is identified as an extreme outlier to the earthquake population. Additionally, the 1998 nuclear tests in India and Pakistan are also identified as outliers, although the 1998 tests are not as unusual as the North African test. Despite the success of the examples shown here, there is a magnitude below which an event will not be distinguished from the earthquake population. This threshold magnitude is important to identify, and we are working to map out this threshold value. The fractal method does not attempt to discriminate between man-made sources; because, there is no reason to believe that these sources are characterized by a fractal distribution.

Nonetheless, the ability to identify events that are inconsistent with the population of earthquakes, which makes up the largest number of seismic events, is of great utility for monitoring purposes. The fractal method relies heavily on complete seismicity catalogues and we are currently working to apply the fractal methodology using regional and local catalogue information. Use of more complete catalogues will allow us to better constrain the fractal models over a wider range of magnitude and distance. I n addition to source characterization for CTBT monitoring, we are adapting the fractal methodology to numerous other seismological problems, including: hazard analysis, estimation of event-occurrence rate as a function of monitoring threshold, and identifying mining activity by its distinct magnitude-spatial distribution.

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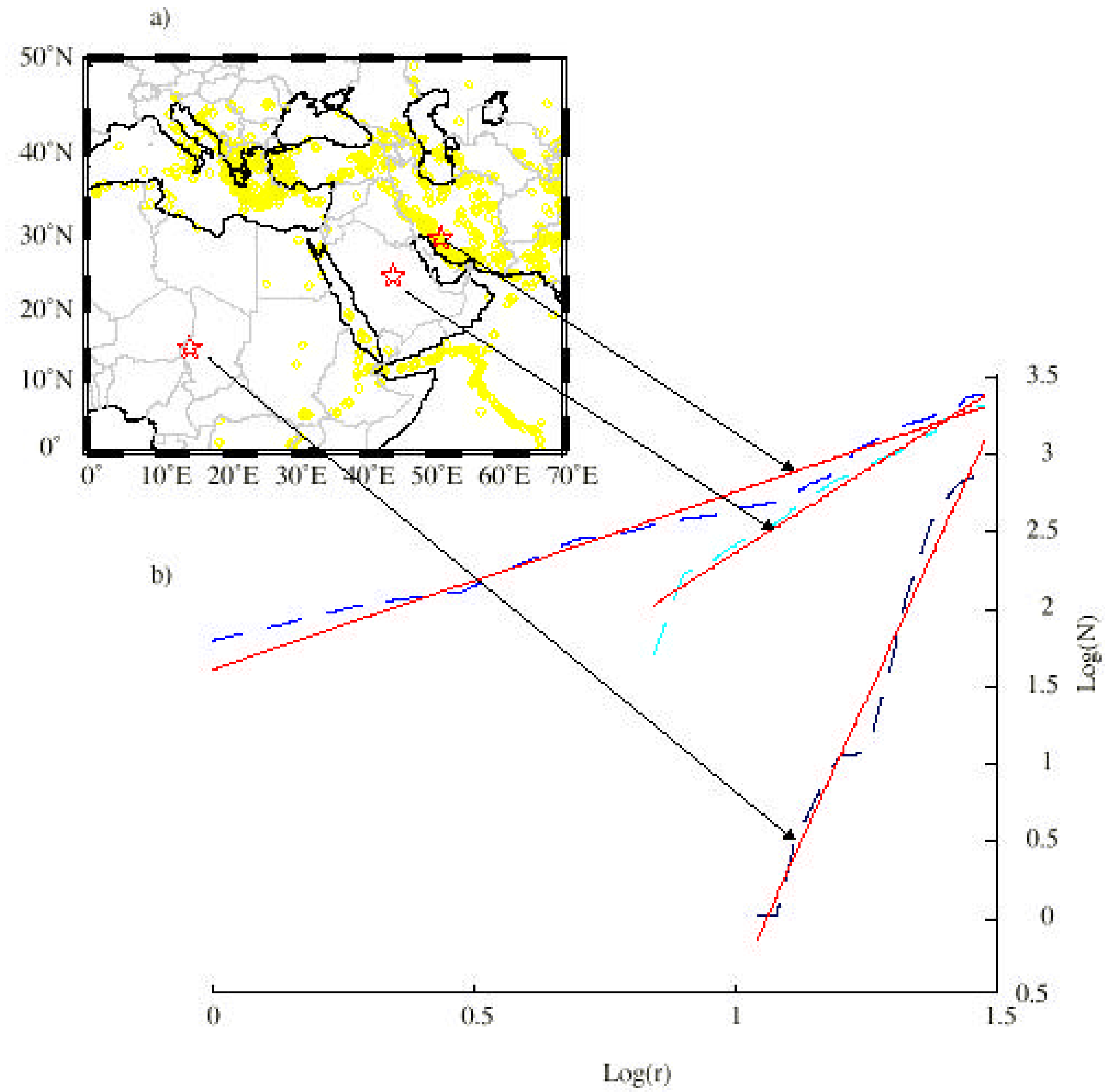

Figure1. Example of fractal models of earthquak e epicenters at three locations with distinctly different seismicity rates. a) Circles are epicenters of catalogue events between magnitude 5 and 6 over a 30 year period. Example locations are shown by stars. b) Fractal models for the three example points. The variable r is the great-circle distance (degrees) from the example point, and N is the number of events occurring inside a disc with radius r. Dashed lines are data curves and straight lines are fractal parameterizations. Note the good fit of the model to the data and the distinctly different slope (fractal dimension) and intercept (overall rate of seismicity) at each of the points.

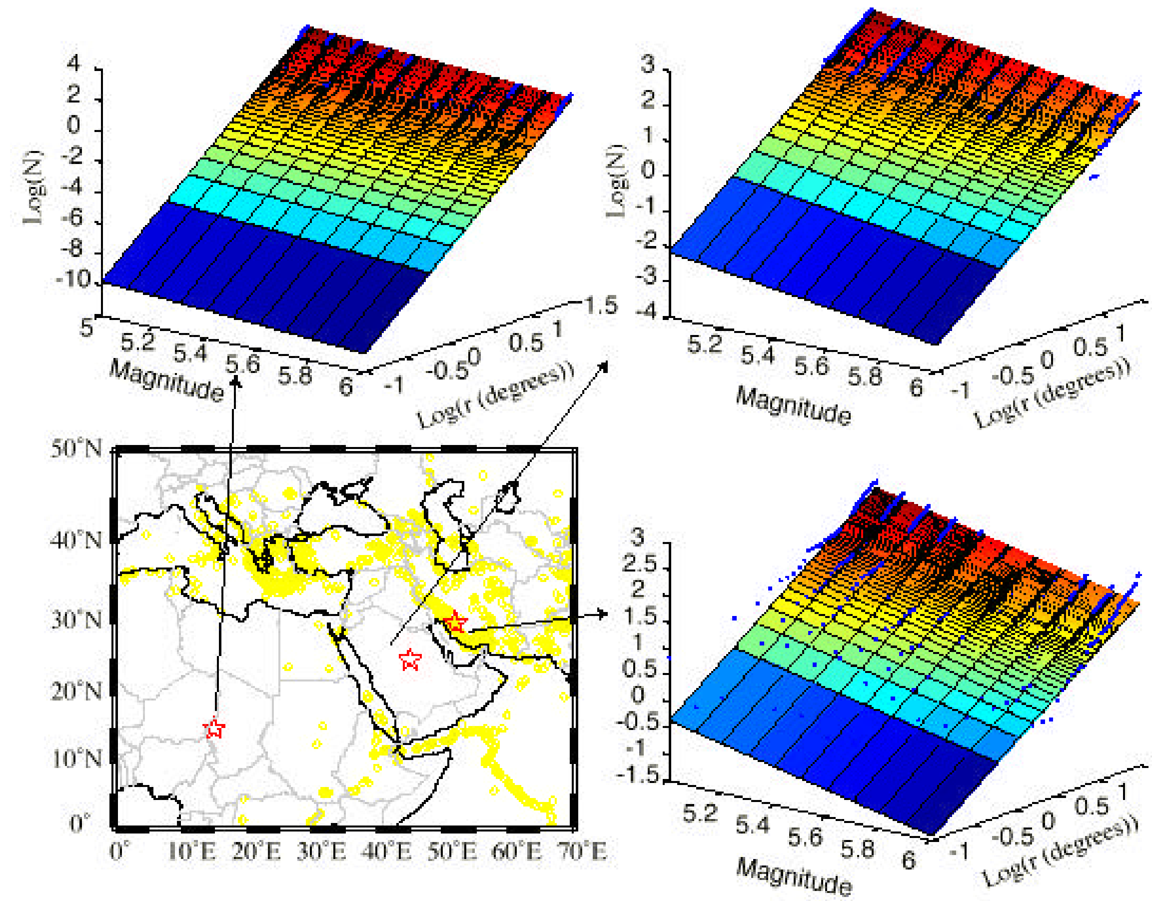

Figure2. Example of joint magnitude-spatial fractal dristrib utions at three locations with distinctly different seismicity rates. The map is the same as Figure 1. Each of the 3- dimensional planes is a fractal model with independent variables of magnitude and distance from the example point. The dependent variable (N) is the number of events occurring inside a disc with radius r at each magnitude. The plotted points are the observations to which the plane is fit. Note the good fit of the model to the data and the vastly differing numbers of events predicted at each example location.

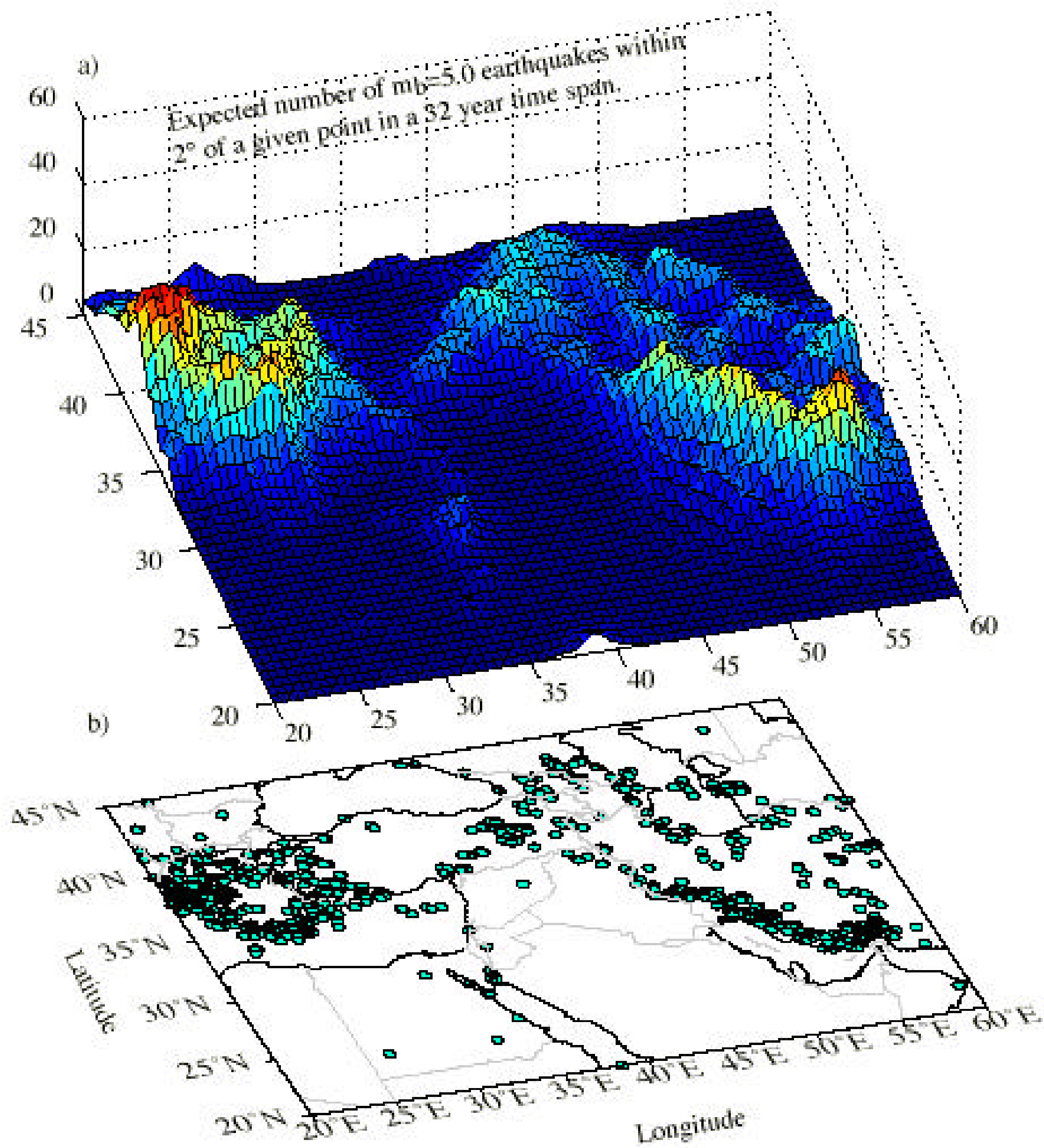

Figure 3. Using fractal models, a map sho wing the expected number of earthquakes of a given magnitude occurring within a given radius from each point can be constructed. a) This map is constructed using the ISC catalogue between 1964 and 1990. The large expected value on the west side of the map area is attributed to Aegean seismicity. The Zagros seismicity is seen as the linear trend in the eastern portion of the map. b) Seismicity in the ISC catalogue that was used to construct the map shown in section (a).

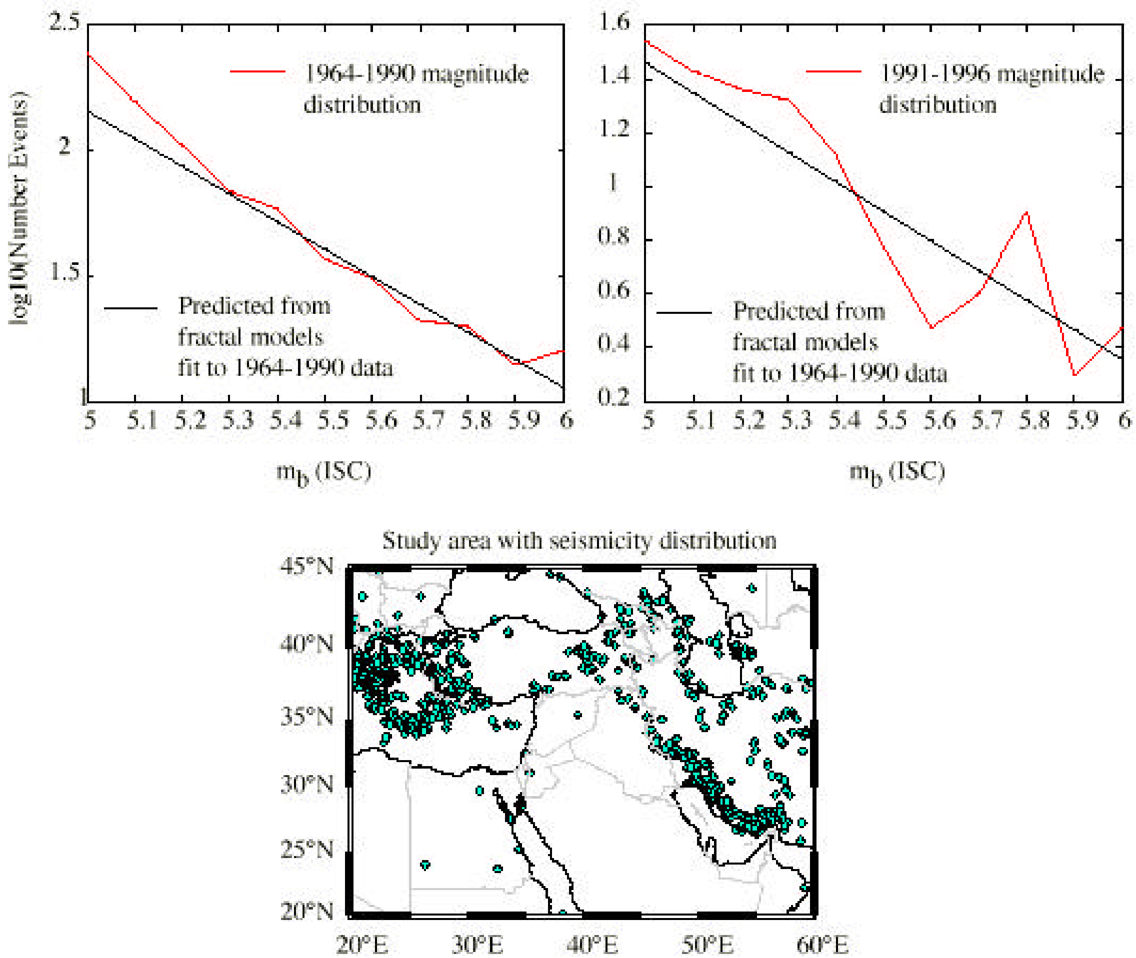

Figure 4. The number of e vents in a region is well matched by determining fractal models on a grid of points that covers the region and summing the number of events predicted at each node. In this procedure the seismicity catalogue is broken down into fractal models at each grid point (Figure3). Then the expected number of events at each point is summed to reconstruct that magnitude distribution. a) The summing procedure fits the data used to produce the fractal models. (b) Summing also predicts the numbers of events in subsequent years. c) The study area for this example is shown in the bottom panel.

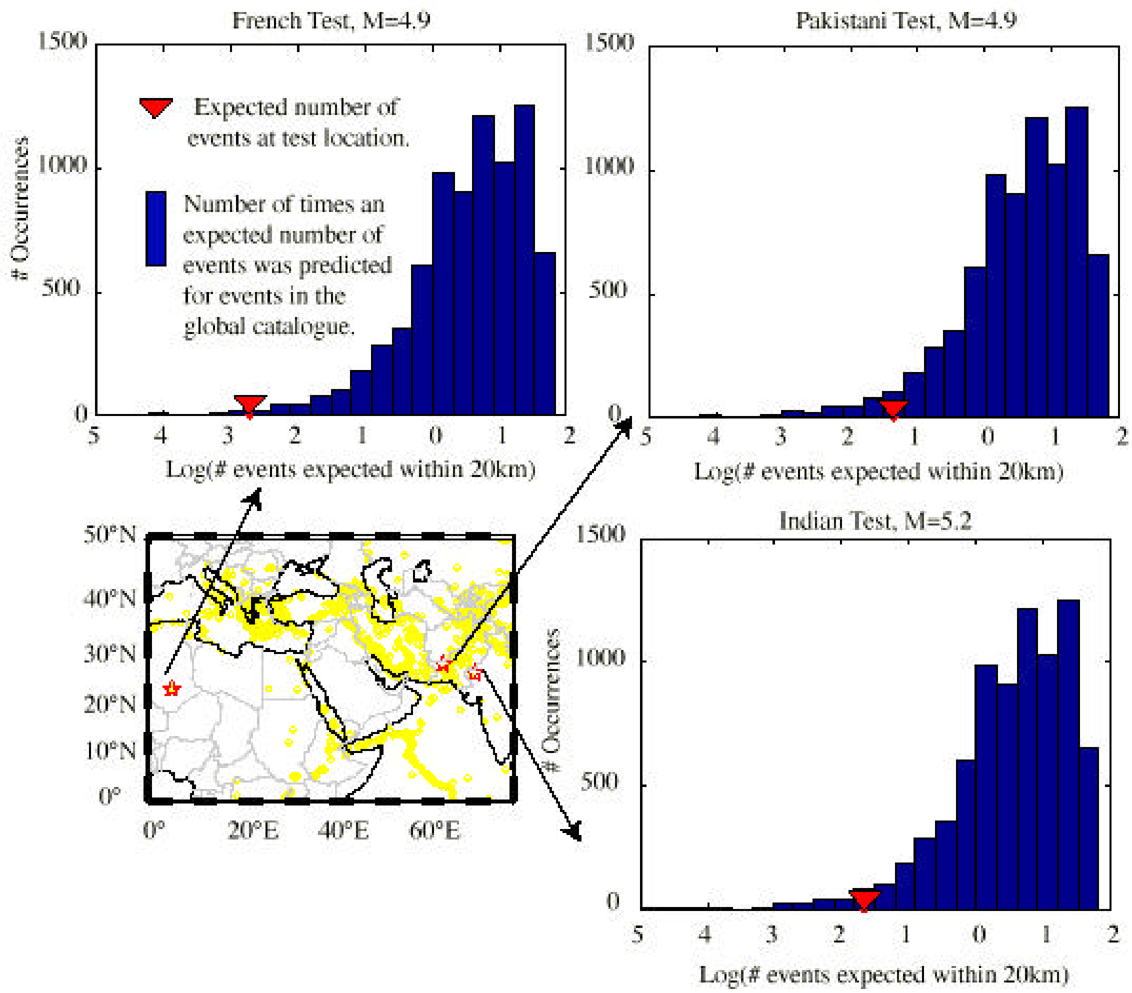

Figure 5. Example of outlier characterization for three nuclear tests. The bar graphs are constructed by: 1) using all the events in the global catalogue (30 years of data) with magnitude equal to the nuclear test, 2) calculating the expected number of earthquakes (with magnitude equal to the nuclear test) within 20 km (arbitrary) of each catalogue epicenter, 3) binning the number of occurrences of the predicted values. This provides an empirical distribution of the variation in fractal model predictions in cases where an event actually occurred. The number of events predicted within a 20 km radius of the nuclear test is then plotted on the distribution for comparison.