Earthquake forecasting and its verification

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Abstract. No proven method is currently available for the reliable short time prediction of earthquakes (minutes to months). However, it is possible to make probabilistic hazard assessments for earthquake risk. These are primarily based on the association of small earthquakes with future large earthquakes. In this paper we discuss a new approach to earthquake forecasting. This approach is based on a pattern informatics (PI) method which quantifies temporal variations in seismicity. The output is a map of areas in a seismogenic region (“hotspots”) where earthquakes are forecast to occur in a future 10-year time span. This approach has been successfully applied to California, to Japan, and on a worldwide basis. These forecasts are binary—an earthquake is forecast either to occur or to not occur. The standard approach to the evaluation of a binary forecast is the use of the relative operating characteristic (ROC) diagram, which is a more restrictive test and less subject to bias than maximum likelihood tests. To test our PI method, we made two types of retrospective forecasts for California. The first is the PI method and the second is a relative intensity (RI) forecast based on the hypothesis that future earthquakes will occur where earthquakes have occurred in the recent past. While both retrospective forecasts are for the ten year period 1 January 2000 to 31 December 2009, we performed an interim analysis 5 years into the forecast. The PI method outperforms the RI method under most circumstances.

1 Introduction

Earthquakes are the most feared of natural hazards because they occur without warning. Hurricanes can be tracked, floods develop gradually, and volcanic eruptions are preceded by a variety of precursory phenomena. Earthquakes, however, generally occur without any warning. There have been a wide variety of approaches applied to the forecast-
October 2004. A global forecast, presented at the early December 2004 meeting of the American Geophysical Union, successfully forecast the locations of the 23 December 2004, M=8.1 Macquarie Island earthquake, and the 26 December 2004 M=9.0 Sumatra earthquake. Before presenting further details of these studies we will give a brief overview of the current state of earthquake prediction and forecasting.

2 Empirical approaches

Empirical approaches to earthquake prediction rely on local observations of precursory phenomena in the vicinity of the earthquake to be predicted. It has been suggested that one or more of the following phenomena may indicate a future earthquake: 1) precursory increase or decrease in seismicity in the vicinity of the origin of a future earthquake rupture, 2) precursory fault slip that leads to surface tilt and/or displacements, 3) electromagnetic signals, 4) chemical emissions, and 5) changes in animal behavior.

Examples of successful near-term predictions of future earthquakes have been rare. A notable exception was the prediction of the M=7.3 Haicheng earthquake in northeast China that occurred on 4 February 1975. This prediction led to the evacuation of the city which undoubtedly saved many lives. The Chinese reported that the successful prediction was based on foreshocks, groundwater anomalies, and animal behavior. Unfortunately, a similar prediction was not made prior to the magnitude M=7.8 Tangshan earthquake that occurred on 28 July 1976 (Utsu, 2003). Official reports placed the death toll in this earthquake at 242,000, although unofficial reports placed it as high as 655,000.

In order to thoroughly test for the occurrence of direct precursors the United States Geological Survey (USGS) initiated the Parkfield (California) Earthquake Prediction Experiment in 1985 (Bakun and Lindh, 1988; Kanamori, 1989). Earthquakes on this section of the San Andreas had occurred in 1857, 1881, 1901, 1922, 1934, and 1966. It was expected that the next earthquake in this sequence would occur by the early 1990’s, and an extensive range of instrumentation was installed. The next earthquake in the sequence finally occurred on 28 September 2004. No precursory phenomena were observed that were significantly above the background noise level. Although the use of empirical precursors cannot be ruled out, the future of those approaches does not appear to be promising at this time.

3 Statistical and statistical physics approaches

A variety of studies have utilized variations in seismicity over relatively large distances to forecast future earthquakes. The distances are large relative to the rupture dimension of the subsequent earthquake. These approaches are based on the concept that the earth’s crust is an activated thermodynamic system (Bakun et al., 2003). Among the evidence for this behavior is the continuous level of background seismicity in all seismographic areas. About a million magnitude two earthquakes occur each year on our planet. In southern California about a thousand magnitude two earthquakes occur each year. Except for the aftershocks of large earthquakes, such as the 1992 M=7.3 Landers earthquake, this seismic activity is essentially constant over time. If the level of background seismicity varied systematically with the occurrence of large earthquakes, earthquake forecasting would be relatively easy. This, however, is not the case.

There is increasing evidence that there are systematic precursory variations in some aspects of regional seismicity. For example, it has been observed that there is a systematic variation in the number of magnitude M=3 and larger earthquakes prior to at least some magnitude M=5 and larger earthquakes, and a systematic variation in the number of magnitude M=5 and larger earthquakes prior to some magnitude M=7 and larger earthquakes. The spatial regions associated with this phenomena tend to be relatively large, suggesting that an earthquake may resemble a phase change with an increase in the “correlation length” prior to an earthquake (Bakun et al., 1998). There have also been reports of anomalous quiescence in the source region prior to a large earthquake, a pattern that is often called a “Mogi Donut” (Mogi, 1985; Kanamori, 2003; Hynds and Habermann, 1988; Wyss, 1997).

Many authors have noted the occurrence of a relatively large number of intermediate-sized earthquakes prior to a great earthquake. A specific example was the sequence of earthquakes that preceded the 1906 San Francisco earthquake (Sykes and Jumé, 1990). This seismic activation has been quantified as a power law increase in seismicity prior to earthquakes (Bozeman et al., 1998; Jumé and Sykes, 1999; Bufe and Varnes, 1993; Bufe et al., 1994; Brehm and Braile, 1998; 1999; Main, 1999; Robinson, 2001; Bowman and King, 2001; Yang et al., 2001; King and Bowman, 2003; Bowman and Sammis, 2004; Sammis et al., 2004). Unfortunately the success of these studies has depended on knowing the location of the subsequent earthquake.

A series of statistical algorithms to make intermediate term earthquake predictions have been developed by a Russian group under the direction of V. I. Keilis-Borok using pattern recognition techniques (Keilis-Borok, 1990, 1996). Seismicity in circular regions with diameters of 500 km was analyzed. Based primarily on seismic activation, earthquake alarms were issued for one or more regions, with the alarms generally lasting for three years. Alarms have been issued regularly since the mid 1980’s and scored two notable successes: the prediction of the 1988 Armenian earthquake and the 1989 Loma Prieta earthquake. While a reasonably high success rate has been achieved, there have been some notable misses including the recent M=9.0 Sumatra and M=8.1 Macquarie Island earthquakes.

More recently, this group has used chains of premonitory earthquakes as the basis for issuing alarms (Shebalin et al., 2004; Keilis-Borok et al., 2004). This method successfully
Earthquakes are caused by displacements on preexisting faults. Most earthquakes occur at or near the boundaries between the near-rigid plates of plate tectonics. Earthquakes in faults. Most earthquakes occur at or near the boundaries between the near-rigid plates of plate tectonics. Earthquakes in California are associated with the relative motion between the Pacific plate and the North American plate. Much of this motion is taken up by displacements on the San Andreas fault, but deformation and earthquakes extend from the Rocky Mountains on the east into the Pacific Ocean adjacent to California on the west. Clearly this deformation and the associated earthquakes are extremely complex.

It is now generally accepted that earthquakes are examples of deterministic chaos [Turcotte, 1997]. Some authors [Geller et al., 1997; Geller, 1997] have argued that this chaotic behavior precludes the prediction of earthquakes. However, weather is also chaotic, but forecasts can be made. Weather forecasts are probabilistic in the sense that weather cannot be predicted exactly. One such example is the track of a hurricane. Probabilistic forecasts of hurricane tracks are routinely made; sometimes they are extremely accurate while at other times they are not. Another example of weather forecasting is the forecast of El Niño events. Forecasting techniques based on pattern recognition and principle components of the sea surface temperature fluctuation time series have been developed that are quite successful in forecasting future El Niños, but again they are probabilistic in nature [Chen et al., 2004]. It has also been argued [Sykes et al., 1999] that chaotic behavior does not preclude the probabilistic forecasting of future earthquakes. Over the past five years our group has developed [Rundle et al., 2002; Tiano et al., 2002a; Rundle et al., 2003; Holliday et al., 2005] a technique for forecasting the locations where earthquakes will occur based on pattern informatics (PI). This type of approach has close links to principle component analysis, which has been successfully used for the forecasting of El Niños.

5 The PI method

Seismic networks provide the times and locations of earthquakes over a wide range of scales. One of the most sensitive networks has been deployed over southern California and the resulting catalog is readily available. Our objective has been to analyze the historical seismicity for anomalous behavior that would provide information on the occurrence of future earthquakes. At this point we are not able to forecast the times of future earthquakes with precision. However, our approach does appear to select the regions where earthquakes are most likely to occur during a future time window. At the present time, this time window is typically taken to be ten years, although it appears that it is possible to utilize shorter time windows.

Our approach divides the seismogenic region to be studied into a grid of square boxes whose size is related to the magnitude of the earthquakes to be forecast. The rates of seismicity in each box are studied to quantify anomalous behavior. The basic idea is that any seismicity precursors represent changes, either a local increase or decrease of seismic activity, so our method identifies the locations in which these changes are most significant during a predefined change interval. The subsequent forecast interval is the decadal time window during which the forecast is valid. The box size is selected to be consistent with the correlation length associated with accelerated seismic activity [Bowman et al., 1998], and the minimum earthquake magnitude considered is the lower limit of sensitivity and completeness of the network in the region under consideration.

The detailed utilization of the PI method that we have used for earthquake forecasting is as follows:

1. The region of interest is divided into $N_B$ square boxes with linear dimension $\Delta x$. Boxes are identified by a subscript $i$ and are centered at $x_i$. For each box, there is a time series $N_i(t)$, which is the number of earthquakes per unit time at time $t$ larger than the lower cut-off magnitude $M_c$. The time series in box $i$ is defined between a base time $t_b$ and the present time $t$.

2. All earthquakes in the region of interest with magnitudes greater than a lower cutoff magnitude $M_c$ are included. The lower cutoff magnitude $M_c$ is specified in order to ensure completeness of the data through time, from an initial time $t_0$ to a final time $t_2$.

3. Three time intervals are considered:

   (a) A reference time interval from $t_0$ to $t_1$.

   (b) A second time interval from $t_b$ to $t_2$, $t_2 > t_1$. The change interval over which seismic activity changes are determined is then $t_2 - t_1$. The time $t_0$ is chosen to lie between $t_b$ and $t_1$. Typically we take $t_0 = 1932$, $t_1 = 1990$, and $t_2 = 2000$. The objective is to quantify anomalous seismic activity in the change interval $t_1$ to $t_2$ relative to the reference interval $t_0$ to $t_1$.

   (c) The forecast time interval $t_2$ to $t_3$, for which the forecast is valid. We take the change and forecast intervals to have the same length. For the above example, $t_3 = 2010$.

4. The seismic intensity in box $i$, $I_i(t_b, t)$, between two times $t_b < t$, can then be defined as the average number of earthquakes with magnitudes greater than $M_c$ that occur in the box per unit time during the specified time.
5. In order to compute the intensities from different time intervals, we require that they have the same statistical properties. We therefore normalize the seismic intensities by subtracting the mean seismic activity of all boxes and dividing by the standard deviation of the seismic activity in all boxes. The statistically normalized seismic intensity of box $i$ during the time interval $t_b$ to $t$ is then defined by

$$I_i(t_b, t) = \frac{1}{t - t_b} \sum_{t'=t_b}^{t} N_i(t'),$$

where the sum is performed over increments of the time series, say days.

6. Our measure of anomalous seismicity in box $i$ is the difference between the two normalized seismic intensities:

$$\Delta I_i(t_b, t_1, t_2) = \hat{I}_i(t_b, t_2) - \hat{I}_i(t_b, t_1).$$

7. To reduce the relative importance of random fluctuations (noise) in seismic activity, we compute the average change in intensity, $\Delta I_i(t_0, t_1, t_2)$ over all possible pairs of normalized intensity maps having the same change interval:

$$\Delta I_i(t_0, t_1, t_2) = \frac{1}{t_1 - t_0} \sum_{t_b=t_0}^{t_1} \Delta I_i(t_b, t_1, t_2),$$

where the sum is performed over increments of the time series, which here are days.

8. We define the probability of a future earthquake in box $i$, $P_i(t_0, t_1, t_2)$, as the square of the average intensity change:

$$P_i(t_0, t_1, t_2) = \Delta I_i(t_b, t_1, t_2) \frac{1}{\sigma(t_b, t)}.$$
Fig. 1. Application of the PI method to southern California. Colored areas are the forecast hotspots for the occurrence of M≥5 earthquakes during the period 2000-2010 derived using the PI method. The color scale gives values of the log \( \log_{10} \left( \frac{P}{P_{\text{max}}} \right) \). Also shown are the locations of the seventeen earthquakes with M≥5 that have occurred in the region since 1 January 2000. Fifteen of the seventeen earthquakes were successfully forecast. More details of the earthquakes are given in Table 1.

Table 1. Earthquakes with M≥5 that occurred in the California test region since 1 January 2000. Fifteen of these seventeen earthquakes were successfully forecast. The two missed events are marked with an asterisk.

| Event         | Magnitude | Date       |
|---------------|-----------|------------|
| Big Bear I    | M=5.1     | 10 Feb. 2001 |
| Coso          | M=5.1     | 17 July 2001 |
| Anza I        | M=5.1     | 32 Oct. 2001 |
| Baja          | M=5.7     | 22 Feb. 2002 |
| Gilroy        | M=5.0     | 13 May. 2002 |
| Big Bear II   | M=5.4     | 22 Feb. 2003 |
| San Simeon*   | M=6.5     | 22 Dec. 2003 |
| San Clemente Island* | M=5.2   | 15 June 2004 |
| Bodie I       | M=5.5     | 18 Sept. 2004 |
| Bodie II      | M=5.4     | 18 Sept. 2004 |
| Parkfield I   | M=6.0     | 18 Sept. 2004 |
| Parkfield II  | M=5.2     | 18 Sept. 2004 |
| Arvin         | M=5.0     | 29 Sept. 2004 |
| Parkfield III | M=5.0     | 30 Sept. 2004 |
| Wheeler Ridge | M=5.2     | 16 April 2005 |
| Anza II       | M=5.2     | 12 June 2005 |
| Yucaipa       | M=5.0     | 16 June 2005 |

Fig. 2. Application of the PI method to central Japan. Colored areas are the forecast hotspots for the occurrence of M≥5 earthquakes during the period 2000-2010 derived using the PI method. The color scale gives values of the log \( \log_{10} \left( \frac{P}{P_{\text{max}}} \right) \). Also shown are the locations of the 99 earthquakes with M≥5 that have occurred in the region since 1 January 2000.

7 Forecast verification

Previous tests of earthquake forecasts have emphasized the likelihood test (Kagan and Jackson, 2000; Rundle et al., 2002; Tiampo et al., 2002b, Holliday et al., 2005). These tests have the significant disadvantage that they are overly sensitive to the least probable events. For example, consider two forecasts. The first perfectly forecasts 99 out of 100 events but assigns zero probability to the last event. The second assigns zero probability to all 100 events. Under a likelihood test, both forecasts will have the same skill score of \(-\infty\). Furthermore, a naive forecast that assigns uniform probability to all possible sites will always score higher than a forecast that misses only a single event but is otherwise excellent.
perior. For this reason, likelihood tests are more subject to unconscious bias.

An extensive review on forecast verification in the atmospheric sciences has been given by Joliffe and Stephenson (2003). The wide variety of approaches that they consider are directly applicable to earthquake forecasts as well. The earthquake forecasts considered in this paper can be viewed as binary forecasts by considering the events (earthquakes) as being forecast either to occur or not to occur in a given box. We consider that there are four possible outcomes for each box, thus two ways to classify each red, hotspot, box, and two ways to classify each white, non-hotspot, box:

1. An event occurs in a hotspot box or within the Moore neighborhood of the box (the Moore neighborhood is comprised of the eight boxes surrounding the forecast box). This is a success.

2. No event occurs in a white non-hotspot box. This is also a success.

3. No event occurs in a hotspot box or within the Moore neighborhood of the hotspot box. This is a false alarm.

4. An event occurs in a white, non-hotspot box. This is a failure to forecast.

We note that these rules tend to give credit, as successful forecasts, for events that occur very near hotspot boxes. We have adopted these rules in part because the grid of boxes is positioned arbitrarily on the seismically active region, thus we allow a margin of error of \pm 1 box dimension. In addition, the events we are forecasting are large enough so that their source dimension approaches, and can even exceed, the box dimension meaning that an event might have its epicenter outside a hotspot box, but the rupture might then propagate into the box. Other similar rules are possible but we have chosen these for convenience.

The standard approach to the evaluation of a binary forecast is the use of a relative operating characteristic (ROC) diagram (Swets, 1973; Mason, 2003). Standard ROC diagrams consider the fraction of failures-to-predict and the fraction of false alarms. This method evaluates the performance of the forecast method relative to random chance by constructing a plot of the fraction of failures to predict against the fraction of false alarms for an ensemble of forecasts. Molchan (1997) has used a modification of this method to evaluate the success of intermediate term earthquake forecasts.

The binary approach has a long history, over 100 years, in the verification of tornado forecasts (Mason, 2003). These forecasts take the form of a tornado forecast for a specific location and time interval, each forecast having a binary set of possible outcomes. For example, during a given time window several hours duration, a forecast is issued in which a list of counties is given with a statement that one or more tornadoes will or will not occur. A 2 × 2 contingency table is then constructed, the top row contains the counties in which tornadoes are forecast to occur and the bottom row contains counties in which tornadoes are forecast to not occur. Similarly, the left column represents counties in which tornadoes were actually observed, and the right column represents counties in which no tornadoes were observed.

With respect to earthquakes, our forecasts take exactly this form. A time window is proposed during which the forecast of large earthquakes having a magnitude above some minimum threshold is considered valid. An example might be a forecast of earthquakes larger than $M = 5$ during a period of five or ten years duration. A map of the seismically active region is then completely covered (“tiled”) with boxes of two types: boxes in which the epicenters of at least one large earthquake are forecast to occur and boxes in which large earthquakes are forecast to not occur. In other types of forecasts, large earthquakes are given some continuous probability of occurrence from 0\% to 100\% in each box (Kagan and Jackson, 2000). These forecasts can be converted to the binary type by the application of a threshold value. Boxes having a probability below the threshold are assigned a forecast rating of non-occurrence during the time window, while boxes having a probability above the threshold are assigned a forecast rating of occurrence. A high threshold value may lead to many failures to predict (events that occur where no event is forecast), but few false alarms (an event is forecast at a location but no event occurs). The level at which the threshold is set is then a matter of public policy specified by emergency planners, representing a balance between the prevalence of failures to predict and false alarms.

8 Binary earthquake forecast verification

To illustrate this approach to earthquake forecast verification, we have constructed two types of retrospective binary forecasts for California. The first type of forecast utilizes the PI method described above. We apply the method to southern California. The first type of forecast utilizes the PI method described above. We apply the method to southern California. The second type of forecast utilizes the PI method described above. We apply the method to southern California.
California and adjacent regions (32° to 38.3° N lat, 238° to 245° E long) using a grid of boxes with \( \Delta x = 0.1^\circ \) and a lower magnitude cutoff \( M_c = 3.0 \). For this retrospective forecast we take the initial time \( t_0 = 1932 \), the change interval \( t_1 = 1989 \) to \( t_2 = 2000 \), and the forecast interval \( t_2 = 2000 \) to \( t_3 = 2010 \) [Rundle et al. 2002; Triampo et al. 2002b]. In the analysis given above we considered regions with \( \Delta P \) positive to be hotspots. The PI forecast under the above conditions with \( \Delta P > 0 \) is given in Figure 4B. Hotspots include 127 of the 5040 boxes considered. This forecast corresponds to that given in Figure 4A. The threshold for hotspot activation can be varied by changing the threshold value for \( \Delta P \). A forecast using a higher threshold value is given in Figure 4A. Hotspots here include only 29 of the 5040 boxes considered.

An alternative approach to earthquake forecasting is to use the rate of occurrence of earthquakes in the past. We refer to this type of forecast as a relative intensity (RI) forecast. In such a forecast, the study region is tiled with boxes of size \( 0.1^\circ \times 0.1^\circ \). The number of earthquakes with magnitude \( M \geq 3.0 \) in each box down to a depth of 20 km is determined over the time period from \( t_0 = 1932 \) to \( t_2 = 2000 \). The RI score for each box is then computed as the total number of earthquakes in the box in the time period divided by the value for the box having the largest value. A threshold value in the interval \([0, 1]\) is then selected. Large earthquakes having \( M \geq 5 \) are then considered possible only in boxes having an RI value larger than the threshold. The remaining boxes with RI scores smaller than the threshold represent sites at which large earthquakes are forecast to not occur. The physical justification for this type of forecast is that large earthquakes are considered most likely to occur at sites of high seismic activity.

In order to make a direct comparison of the RI forecast with the PI forecast, we select the threshold for the RI forecast to give the same box coverage given for the PI forecast in Figures 4A and 4B, i.e. 29 boxes and 127 boxes respectively. Included in all figures are the earthquakes with \( M \geq 5 \) that occurred between 2000 and 2005 in the region under consideration.

9 Contingency tables and ROC diagrams

The first step in our generation of ROC diagrams is the construction of the \( 2 \times 2 \) contingency table for the PI and RI forecast maps given in Figure 4. The hotspot boxes in each map represent the forecast locations. A hotspot box upon which at least one large future earthquake during the forecast period occurs is counted as a successful forecast. A hotspot box upon which no large future earthquake occurs during the forecast period is counted as an unsuccessful forecast, or alternately, a false alarm. A white box upon which at least one large future earthquake during the forecast period occurs is counted as a failure to forecast. A white box upon which no large future earthquake occurs during the forecast period is counted as an unsuccessful forecast of non-occurrence.

Verification of the PI and RI forecasts proceeds in exactly the same was as for tornado forecasts. For a given number of hotspot boxes, which is controlled by the value of the probability threshold in each map, the contingency table (see Table 2) is constructed for both the PI and RI maps. Values for the table elements \( a \) (Forecast=yes, Observed=yes), \( b \) (Forecast=yes, Observed=no), \( c \) (Forecast=no, Observed=yes), and \( d \) (Forecast=no, Observed=no) are obtained for each map. The fraction of colored boxes, also called the probability of forecast of occurrence, is \( r = (a + b)/N \), where the total number of boxes is \( N = a + b + c + d \). The hit rate is \( H = a/(a + c) \) and is the fraction of large earthquakes that occur on a hotspot. The false alarm rate is \( F = b/(b + d) \) and is the fraction of non-observed earthquakes that are incorrectly forecast.

To analyze the information in the PI and RI maps, the standard procedure is to consider all possible forecasts together. These are obtained by increasing \( F \) from 0 (corresponding to no hotspots on the map) to 1 (all active boxes on the map are identified as hotspots). The plot of \( H \) versus \( F \) is the relative operating characteristic (ROC) diagram. Varying the threshold value for both the PI and RI forecasts, we have obtained...
Table 2. Contingency tables as a function of false alarm rate. In Table 2A, a threshold value was chosen such that \( F \approx 0.005 \). In Table 2B, a threshold value was chosen such that \( F \approx 0.021 \).

(A) Pattern informatics (PI) forecast

| Forecast | Observed |       |       |
|----------|----------|-------|-------|
|          | Yes      | No    | Total |
| Yes      | (a) 4    | (b) 25 | 29    |
| No       | (c) 13   | (d) 4998 | 5011  |
| Total    | 17       | 5023  | 5040  |

(B) Relative intensity (RI) forecast

| Forecast | Observed |       |       |
|----------|----------|-------|-------|
|          | Yes      | No    | Total |
| Yes      | (a) 2    | (b) 27 | 29    |
| No       | (c) 14   | (d) 4997 | 5011  |
| Total    | 16       | 5024  | 5040  |

Table 2. Contingency tables as a function of false alarm rate. In Table 2A, a threshold value was chosen such that \( F \approx 0.005 \). In Table 2B, a threshold value was chosen such that \( F \approx 0.021 \).

(A) Pattern informatics (PI) forecast

| Forecast | Observed |       |       |
|----------|----------|-------|-------|
|          | Yes      | No    | Total |
| Yes      | (a) 23   | (b) 104 | 127   |
| No       | (c) 9    | (d) 4904 | 4913  |
| Total    | 32       | 5008  | 5040  |

(B) Relative intensity (RI) forecast

| Forecast | Observed |       |       |
|----------|----------|-------|-------|
|          | Yes      | No    | Total |
| Yes      | (a) 20   | (b) 107 | 127   |
| No       | (c) 10   | (d) 4903 | 4913  |
| Total    | 30       | 5010  | 5040  |

tained the values of \( H \) and \( F \) given in Figure 5 blue for the PI forecasts and red for the RI forecasts. The results corresponding to the maps given in Figure 4 and the contingency tables given in Table 2 are given by the filled symbols. The forecast with 29 hotspot boxes (Figure 5A and Table 2A) has \( F_{PI} = 0.00498, H_{PI} = 0.235 \) and \( F_{RI} = 0.00537, H_{RI} = 0.125 \). The forecast with 127 hotspot boxes (Figure 5B and Table 2B) has \( F_{PI} = 0.0207, H_{PI} = 0.719 \) and \( F_{RI} = 0.0213, H_{RI} = 0.666 \). Also shown in Figure 5 is a gain curve (green) defined by the ratio of \( H_{PI}(F) \) to \( H_{RI}(F) \). Gain values greater than unity indicate better performance using the PI map than using the RI map. The horizontal dashed line corresponds to zero gain. From Figure 5 it can be seen that the PI approach outperforms (is above) the RI under many circumstances and both outperform a random map, where \( H = F \), by a large margin.

10 Discussion

The fundamental question is whether forecasts of the time and location of future earthquakes can be accurately made. It is accepted that long term hazard maps of the expected rate of occurrence of earthquakes are reasonably accurate. But is it possible to do better? Are there precursory phenomena that will allow earthquakes to be forecast?

It is actually quite surprising that immediate local precursory phenomena are not seen. Prior to a volcanic eruption, increases in regional seismicity and surface movements are generally observed. For a fault system, the stress gradually increases until it reaches the frictional strength of the fault and a rupture is initiated. It is certainly reasonable to hypothesize that the stress increase would cause increases in background seismicity and aseismic slip. In order to test this hypothesis the Parkfield Earthquake Prediction Experiment was initiated in 1985. The expected Parkfield earthquake occurred beneath the heavily instrumented region on 28 September 2004. No local precursory changes were observed (Lindh, 2005).

In the absence of local precursory signals, the next question is whether broader anomalies develop, and in particular whether there is anomalous seismic activity. It is this question that is addressed in this paper. Using a technique that has been successfully applied to the forecasting of El Niño we have developed a systematic pattern informatics (PI) approach to the identification of regions of anomalous seismic activity. Applications of this technique to California, Japan, and on a world-wide basis have successfully forecast the location of future earthquakes. It must be emphasized that this is not an earthquake prediction. It is a forecast of where future earthquakes are expected to occur during a relatively long time window of ten years. The objective is to reduce the possible future sites of earthquakes relative to a long term hazard assessment map.

Examination of the ROC diagrams indicates that the most important and useful of the suite of forecast maps are those with the least number of hotspot boxes, i.e., those with small values of \( F \). However, for those cases, the corresponding maps do not appear to be particularly useful. For example, the PI map for the 127 hotspot boxes (Figure 5B) has \( F_{PI} = 0.0207 \) and \( H_{PI} = 0.719 \), which correspond to a gain of 2.5. In contrast, the RI map for the same number of hotspot boxes has \( F_{RI} = 0.0213 \) and \( H_{RI} = 0.666 \), which correspond to a gain of 1.6. Thus, the PI approach appears to be more effective in identifying areas where earthquakes are likely to occur, even though the gain is lower than that of the RI approach.
values of the false alarm rate, $F$. A relatively high proportion of these hotspot boxes represent locations of future large earthquakes, however these maps also have a larger number of failures-to-forecast. Exactly which forecast map(s) to be used will be a decision for policy-makers, who will be called upon to balance the need for few false alarms against the desire for the least number of failures-to-forecast.

Finally, we remark that the methods used to produce the forecast maps described here can be extended and improved. We have found modifications to the procedures described in Section 5 that allow the PI map to substantially outperform the RI map as indicated by the respective ROC diagrams. These methods are based on the approach of: 1) starting with the RI map, and introducing improvements using the steps described for the PI method; and 2) introducing an additional averaging step. This new method and its results will be described in a future publication.

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