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Assessing performances of pattern informatics method variants: a comparative analysis in Zagros, Iran

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Summary
Iran is one of the most seismically active regions in the world. Considering the growing field of earthquake prediction, it seems to be one of the strategies for reducing earthquake damage and managing crises during earthquakes. Given its successful application in various parts of the world, we examined the performance of the Pattern Informatics (PI) method in forecasting earthquakes in Iran's Zagros region. The PI method has a suitable physical basis and clarity in computational procedures. Unlike many other methods, it does not require processing such as windowing or declustering of earthquake catalogs. It considers the seismic patterns of quiescence and anomalous activity without predefined conditions or patterns. The main criterion in this method is the number of events exceeding a specific threshold and counted in regional cells that have been networked using a particular algorithm. In the modified method, besides counting the earthquakes in the central cell, the effects of eight neighboring cells are also considered, influencing the probability of an earthquake event in the central cell. This study investigates the application of the original and modified global versions of this method to the selected seismic catalogs of Iran. To reduce the effect of varying seismic nature and to prevent errors arising from different averaging methods in the seismic regions of Iran with diverse tectonic characteristics, the Zagros tectonic province was chosen based on the division of Iran's provinces.

In this tectonic province, retrospective predictions were conducted along with evaluations and comparisons of the results to validate the method. The results showed that with acceptable spatial accuracy, this method could be used to predict earthquakes larger than the catalog's completeness threshold. For this purpose, the success rate and false alarm rate were calculated by changing the cell dimensions and plotting Molchan and ROC (receiver operating characteristic) evaluation diagrams, given that changes in spatial parameters have the most significant impact on the calculations in this method. The optimal method was determined between the original and modified versions with the most suitable cell dimensions. Based on the results, the original PI method with a $\Delta x = 0.3°$ grid showed the best evaluation results for the Zagros region.

The catalog used in this study was compiled from the Iranian Seismological Center (ISC) and the International Seismological Center (ISCR) from 1980 to 2021 within the geographical range of 44° to 64° longitude east and 25° to 40° north latitude.

Keywords: Earthquake prediction, Zagros, PI and MPI method, ROC diagram, Molchan diagra

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1 Introduction

Widely, forecasts are regularly created among a variety of methods, including those related to politics, economics, climate, and numerous other fields. A fundamental difficult problem in finding the reliability of these predictions is," How can we effectively differentiate between these projections?" Seismic events, a noticeable category of natural hazards, have historically exacted a disastrous toll in terms of human life, economic stability, and societal well-being. Retrofitting and strengthening structures against earthquakes is the most crucial step in preventing damage from earthquakes. However, earthquake prediction can also provide great assistance in decision-making and crisis management by creating knowledge about probable future earthquakes. Given the complexity of the earthquake generation mechanism and the influence of numerous parameters on earthquake occurrence, predictions can be associated with significant errors. Nevertheless, like any other prediction, by optimizing and refining methods, these errors can be reduced, and more reliable predictions can be made for earthquake occurrence within appropriate time and spatial ranges and with a probable magnitude range.

Scientists have investigated numerous approaches to earthquake prediction, among which the Pattern Informatics (PI) method stands out as a significant contribution. Developed by researchers such as,Tiampo (Tiampo K. , Rundle, McGinnis, & Klein, 2002) , Halliday (Holliday, J. R., K. Z; Nanjo, K. F.; Tiampo, J. B. Rundle; Turcotte, D. L.;, 2005), Chen (Chen, et al., 2006), and Radan (Radan, M. Y; Hamzehloo, H; Peresan, A; Zare, M; Zafarani, H, 2013; Rundle, Klein, Tiampo, & Gross, 2000) over the past three decades. This approach involves analyzing recurring patterns within seismic data to identify potential precursors to earthquakes.

The Pattern Informatics (PI) method is a sophisticated statistical technique that seeks to extract earthquake occurrence patterns and predict medium-term (5-10years) (Holliday, et al., 2005) seismic events by carefully considering both the fundamental physical principles underlying seismic phenomena and historical earthquake catalogs. It detects "hotspots" where stress accumulation correlates with future earthquake activity. Unlike traditional approaches, this method does not require catalog modifications such as declustering, which enables a unique advantage: it preserves the potential influence of all previous seismic events on future earthquake predictions. Consequently, the accuracy of the results is directly correlated with the comprehensiveness and precision of the original earthquake catalog. By developing strategic optimization techniques for the PI method, researchers can potentially enhance the reliability and accuracy of long-term earthquake forecasting.

This approach represents a nuanced statistical framework that integrates historical seismic data with fundamental geophysical understanding to improve predictive capabilities.

The mechanisms and physical foundations of the PI method, considering the behavior of the Earth and the fractures created as a result of earthquake occurrences, can be explained based on models similar to the Ising Model (Rundle, Klein, Tiampo, & Gross, 2000), (Tiampo K. , Rundle, McGinnis, & Klein, 2002). Seismicity occurs repeatedly. Microfractures in rocks are generated due to the application of stress, and as stress increases, these microfractures accumulate and follow an exponential distribution. The gradual accumulation of tectonic stress culminates at a critical threshold, ultimately leading to an earthquake and subsequent stress drop. After that, the cycle is repeated. Therefore, it is hypothesized that future occurrences of these events can be anticipated through a rigorous analysis of historical seismicity patterns. A critical aspect of any predictive model is the ability to quantitatively identify patterns. A critical aspect of any predictive model is the ability to quantitatively assess its performance. The reliability of such forecasts is directly proportional to the reduction of error and the demonstrable capacity to outperform random chance (i.e., a 50% success rate).

The limitations of using the PI method may be related to the inadequate quality of data and the interference of aftershocks with main earthquakes in the catalog. By processing the data (cluster separation, spatial averaging), validating ergodicity, and using hybrid modeling, the impact of these factors can be reduced (Jiang & Wu, 2011). Although this method is still not reliable for short-term predictions, advancements in improving results could enhance its role in assessing potential short-term risk.

A prospective forecast for California, spanning the years 2000 to 2010, was published by Rundle (Rundle, Tiampo, Klein, & Sá Martins, 2002) in 2002, based on the PI methodology. Of the 39 earthquakes observed within this period, 37 occurred either inside or within a single box unit (approximately 11 km) of the predicted warning boxes, with only two events occurring outside these areas. Successful retrospective evaluations of the The Mw 7.6 Chi-Chi earthquake in 1999 (Kossobokov, 2006), the Mw 7.2 Kobe earthquake in 1995 (Nanjo K. Z., Rundle, Holliday, & Torcotte, 2006), and the Mw 6.8 Niigata, Japan earthquake in 2004 (Nanjo K. , Rundle, Holliday, & Turcotte, 2006) provide more evidence of the effectiveness of the PI approach. In the parts that follow, several suggested iterations of the pattern informatics method will be assessed, and a means to use it to lower the error in seismic early warning will be discussed. By doing so, we aim to contribute to the advancement of seismological methods that can effectively and promptly assist in the mitigation of seismic hazards.

2 Methodology

A six-step computational procedure makes up the original PI method (Rundle, Turcotte , Shcherbakov , Klein , & ammis , 2003), (Tiampo K. , Rundle, McGinnis, & Klein, 2002). The study area is divided into square boxes of size Δx. This method measures spatial-temporal changes in seismology by analyzing a catalog of earthquakes in a region (Tiampo K. , Rundle, McGinnis, & Klein, 2002). The earthquake catalog is positioned starting at $\mathrm{t_0}$. Three time windows are taken into consideration, as shown in Fig. 1: the reference window $(\mathrm{t_b}, \mathrm{t_1})$, the comparison window $(\mathrm{t_b}, \mathrm{t_2})$, and the forecasting window $(\mathrm{t_2}, \mathrm{t_3})$.

The seismic intensity within each box is calculated by averaging the number of earthquakes with magnitudes greater than $\mathrm{m_c}$ within the time window $(\mathrm{t_b}, t)$:

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

By normalizing the data in different time windows (1), the seismic anomaly for each box is calculated using the equation (2):

$$\hat{I}_i(t_b,t) = \frac{I_i(t_b,t) - < I_i(t_b,t) >}{\sigma(t_b,t)} \quad (2)$$

$$\Delta I_i(t_b,t_1,t_2) = \hat{I}_i(t_b,t_2) - \hat{I}_i(t_b,t_1) \quad (3)$$

The probability of a future earthquake occurring in a box is represented as (4):

$$P_i(t_b,t_1,t_2) \propto [\Delta \bar{I}_i(t_b,t_1,t_2)]^2 \quad (4)$$

It is defined as $\Delta \bar{I}_i(t_b,t_1,t_2)$, which represents the average seismic intensity, calculated as:

$$\Delta \bar{I}_i(t_b,t_1,t_2) = \frac{1}{t_1 - t_b} \sum_{t_b=t_0}^{t_1} \Delta I_i(t_b,t_1,t_2) \quad (5)$$

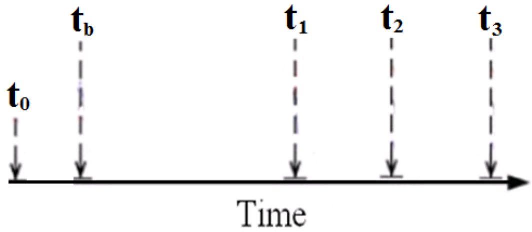

Figure 1. Time windows in PI method((H UAI - ZHONG, et al., 2011))

The final probability of an earthquake occurring in each box is given by:

$$\Delta P_i(t_b,t_1,t_2) = P_i(t_b,t_1,t_2) - < P_i(t_b,t_1,t_2) \quad (6)$$

It has been calculated that $< P_i(t_b,t_1,t_2) >$ represents the average probability for all boxes. Hotspots are identified for boxes where $\Delta P_i(t_b,t_1,t_2) > 0$ is calculated. Since magnitudes are squared in the probability calculations, the hotspots can indicate either an increase or a decrease in seismic activity (i.e., a precursor quiescence) during the specified time interval.

There are two main ways to assess whether earthquake prediction was successful or not. The first way success in prediction is defined is by the occurrence of an earthquake within the warning box and the absence of an earthquake within the white boxes; if not, it is a failure of the prediction (Strategy 1). The second way takes into account the occurrence and non-occurrence of target earthquakes when calculating prediction success and failure rates by considering the eight neighboring boxes of the central box as the Moore neighborhood. The number of successes and failures is then extended to include the earthquakes that occur within these neighboring boxes (Strategy 2). (Fig. 2)

A modified PI method, building upon the original formulation, has been introduced with alterations to the computational procedure (Holliday, J. R., K. Z; Nanjo, K. F.; Tiampo, J. B. Rundle; Turcotte, D. L.;, 2005), (Nanjo K. , Rundle, Holliday, & Turcotte, 2006), (Rundle J. B., 2008), (Tiampo K. , Rundle, Klein, & Holliday, 2006). This approach retains the same temporal windows and regional grid configuration as the original method. However, the calculation of seismic intensity within each cell differs. Specifically, the seismic intensity (I) in each cell is computed as the average occurrence of earthquakes with magnitudes greater than m_c within a central cell and its eight neighboring cells (Moore neighborhood).

$$I(x_i,t_b,t) = \frac{1}{(t - t_b)} \int_{t_b}^{t} n(x_i,t)dt \quad (7)$$

In the above equation, $n(x_i, t)$ represents the number of earthquakes that have occurred within the central cell and its eight adjacent cells. Ultimately, by obtaining the probability of event occurrence, the hotspot boxes are identified. Similar to the original, in the modified version the prediction success and failure rates can be evaluated using two distinct approaches.

Since evaluating forecast results is essential to determining their validity and quality, we go on to discuss two tried-and-true techniques for evaluating predictive model performance. One approach to evaluating the performance of this method involves constructing a Molchan diagram (Zhang, et al., 2021). In this diagram the number of prediction failures (earthquakes that occurred but were not predicted) is plotted against the ratio of alarm to total study area. The diagram displays 95% and 99% confidence curves along with a diagonal line that represents the outcome of totally random guess.It is evident that as the data points from these curves converge towards the origin, the results increasingly diverge from a random guess, indicating a prediction with reduced uncertainty.

Another approach is to plot the ROC curves. This well-established method can be employed to compare the optimality of grid dimensions in the PI method. Considering that this method is a binary approach (grid-based regional analysis and earthquake occurrence as yes or no) and considering the obtained data regarding the accuracy of earthquake warnings issued for each grid cell, utilizing ROC curves is practical for comparative purposes.

In the construction of this diagram, two quantities are plotted against each other: the success prediction rate (the number of predicted events divided by the total number of events) and the false alarm rate (the ratio of warning boxes in which none of the target earthquakes occurred to the total number of boxes). The upper left corner of this diagram indicates a prediction without any false alarms. Therefore, the closer the results are to the upper left corner of the diagram, the more skillful the prediction is. The ROC curve is a step plot where an optimal prediction is indicated by results lying above the diagonal line. Additionally, when comparing curves corresponding to different prediction methods, the method with the larger area under the curve is considered superior.

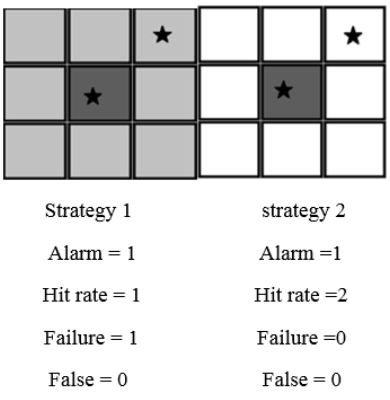

Figure 2. representation of strategies for forecast evaluation(strategy 1:an earthquake warning has been issued for one cell (colored), the cells that include the earthquakes that have occurred (the cells marked with a star)=2,the hit rate in prediction=1,the failure rate=1 and no false warning has been issued (false=0).strategy 2: :an earthquake warning has been issued for one cell (colored),considering the proximity of the cells, the probability of an earthquake event may also exist in neighboring cells, the cells that include the earthquakes that have occurred (the cells marked with a star)=2,the hit rate in prediction=2,the failure rate=0 and no false warning has been issued (false=0).(The authors).

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3 Study region and data sets

To apply the PI method for earthquake forecasting in Iran, a comprehensive catalog was compiled by merging the Iranian Broadband Seismological Network catalog (continuous data on earthquakes in Iran since 1900 AD) with data from the Iranian Seismological Center (ISC) from 1980 to 2021. We have also used the Bafrouei (Mousavi-Bafrouei & Babaie Mahani, 2020) catalogue to reduce errors. The geographical scope covered the area bounded by 44°E to 64°E and 25°N to 40°N.Due to the incompleteness of the earthquakes in the catalog and the significant errors in the locations of the earthquakes in the initial section of the catalog, the processing and calculation of the index PI have used a portion of the catalog that includes from 1996 onward.

To ensure a more accurate and homogeneous earthquake catalog in terms of physical rupture mechanisms, the concept of seismogenic provinces was employed to define the geographical scope and prepare the data. Considering the frequency of earthquakes and the volume of available data, the Zagros seismogenic province was selected, according to the seismotectonic provinces map by Mirzaei (Mirzaei, N; Mengtan, G; Yuntai, C, 1998). The completeness magnitude for this region was determined to be $m_c = 4.5$. (fig. 3)

4 Application of PI and MPI method

The initial version of the PI method was applied to the Zagros seismotectonic province, taking into account the time windows listed in table 1. To enhance spatial prediction accuracy, the approach was tested across 16 time intervals using two strategies with varying cell sizes (Δx = 0.1, 0.2, 0.3, 0.4, 0.5 degrees).

For comparison purposes, the original PI method was also compared to the MPI version, which incorporates an optimized algorithm using the same regional grid and time intervals as the PI method. The evaluation results are presented in Molchan and ROC diagrams in fig. 4 to fig. 11.Figures 4 and 6 show the evaluation charts for the PI method employing two strategies at the same grid sizes. Figures 8 and 10 illustrate the evaluation charts for the Mulchan method concerning the MPI method with similar strategies applied to the PI version and utilizing the same grid cell sizes. To better evaluate and compare the results, the ROC charts for the PI method with two strategies (Figures 5 and 7) and the ROC for the MPI method are also depicted in Figures 9 and 11.

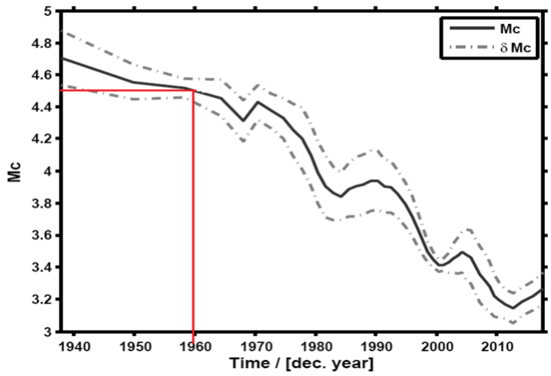


Figure 3. cumulative distribution histogram of earthquakes and the calculation of m_c.

Table 1. consecutive time intervals for analysis of results (5-year prediction period).

Test Num.	Beginning of catalog	Beginning of change interval(t_1)	End of the change interval(t_2)	End of prediction interval(t_3)
1	1980	1996	2001	2006
2	1980	1997	2002	2007
3	1980	1998	2003	2008
4	1980	1999	2004	2009
5	1980	2000	2005	2010
6	1980	2001	2006	2011
7	1980	2002	2007	2012
8	1980	2003	2008	2013
9	1980	2004	2009	2014
10	1980	2005	2010	2015
11	1980	2006	2011	2016
12	1980	2007	2012	2017
13	1980	2008	2013	2018
14	1980	2009	2014	2019
15	1980	2010	2015	2020
16	1980	2011	2016	2021

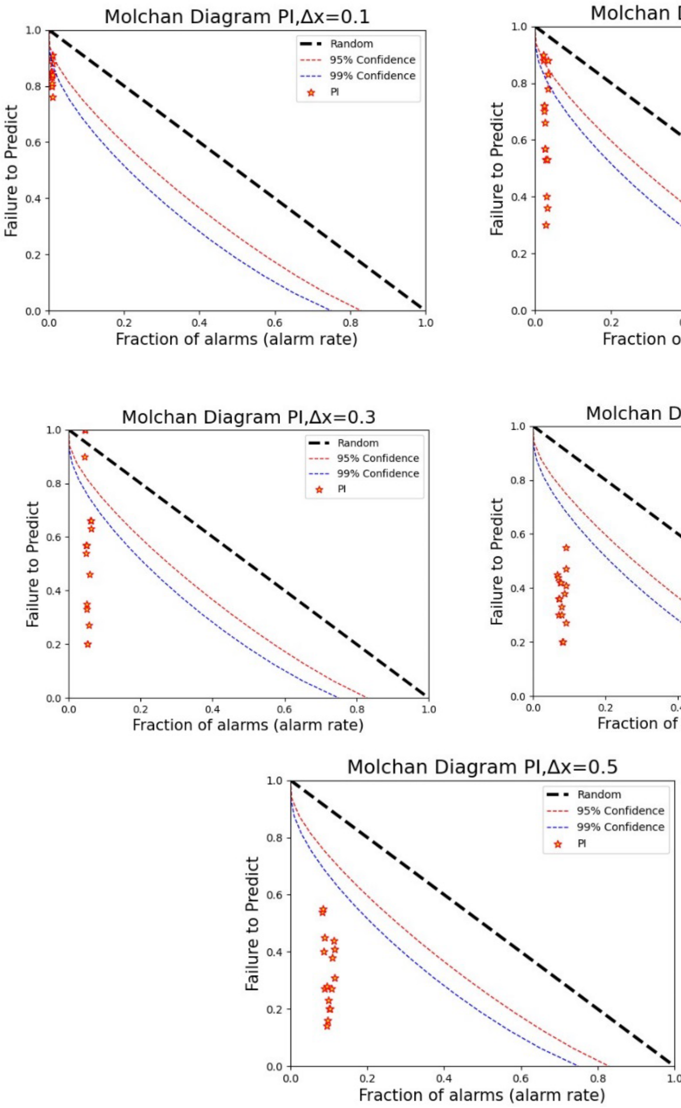


Figure 4. Molchan chart for performance evaluation of original PI (strategy 1) on Δx= 0.1,0.2,0.3,0.4,0.5.

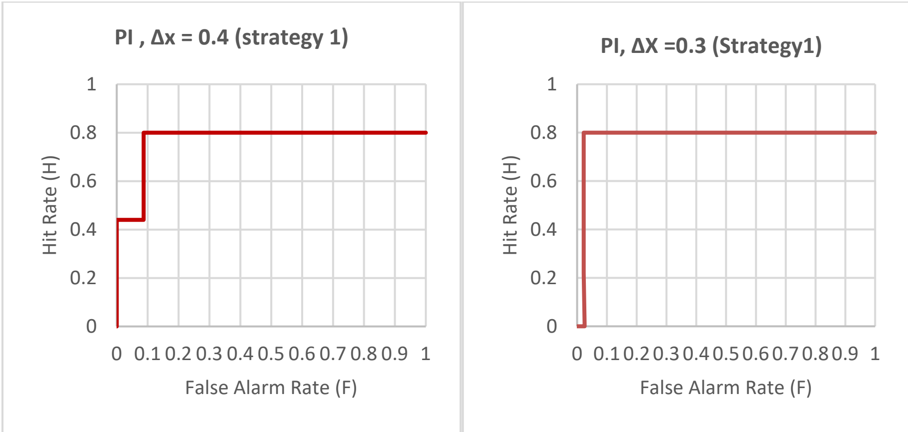


Figure 5. Roc plot for performance comparison of original PI (strategy 1) on Δx= = 0.1,0.2,0.3,0.4,0.5.

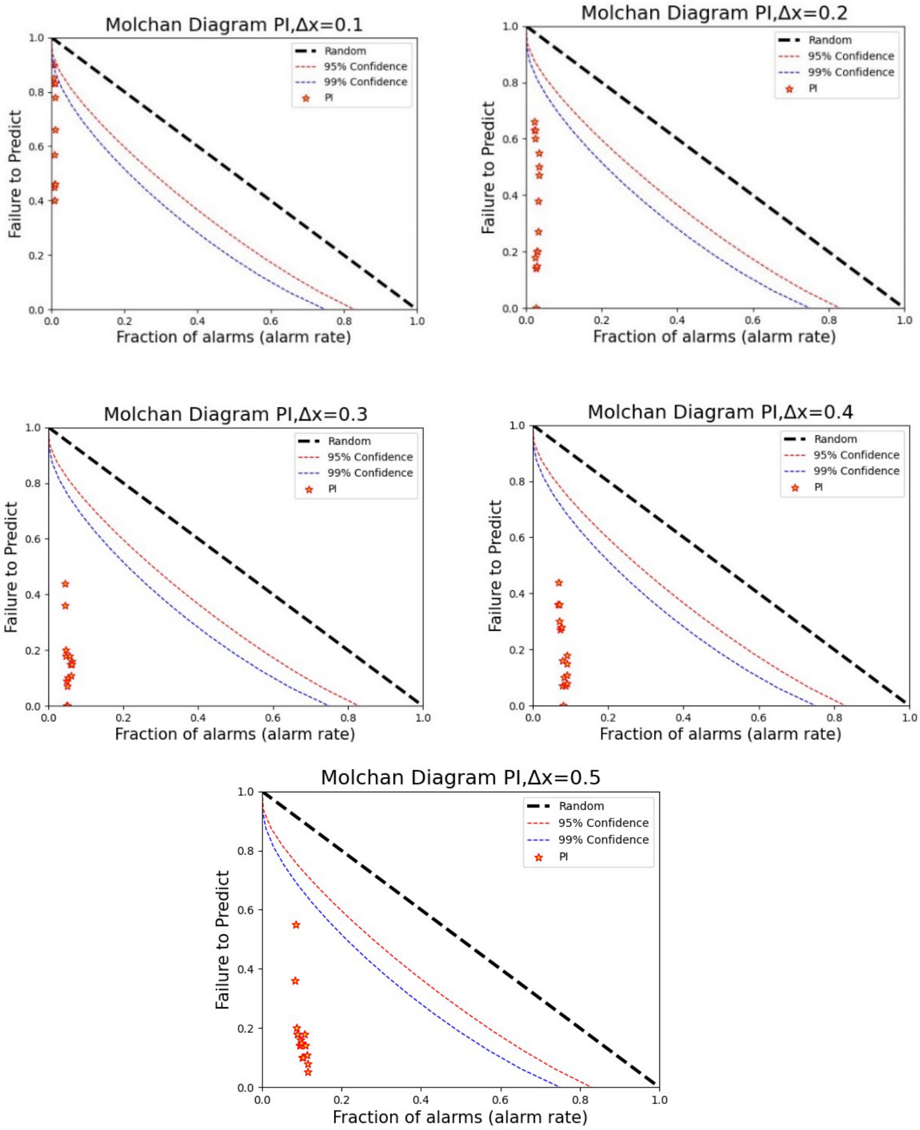


Figure 6. Molchan chart for performance evaluation of original PI (strategy 2) on Δx= 0.1,0.2,0.3,0.4,0.5.

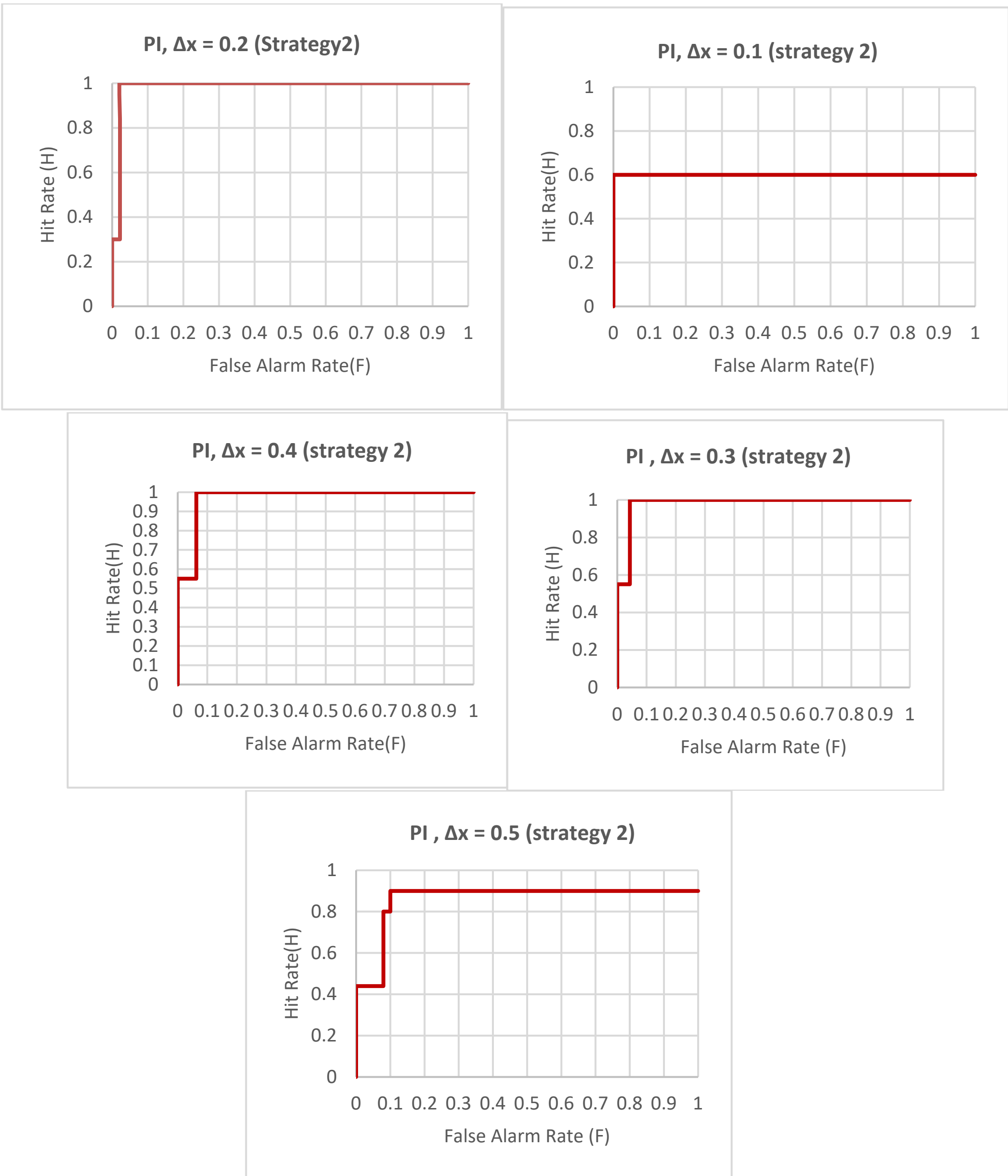
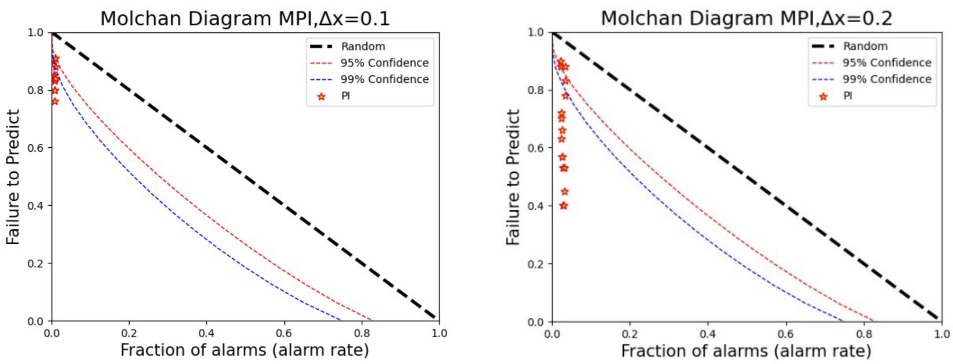


Figure 7. Roc plot for performance comparison of original PI (strategy 2) on Δx= 0.1,0.2,0.3,0.4,0.5.



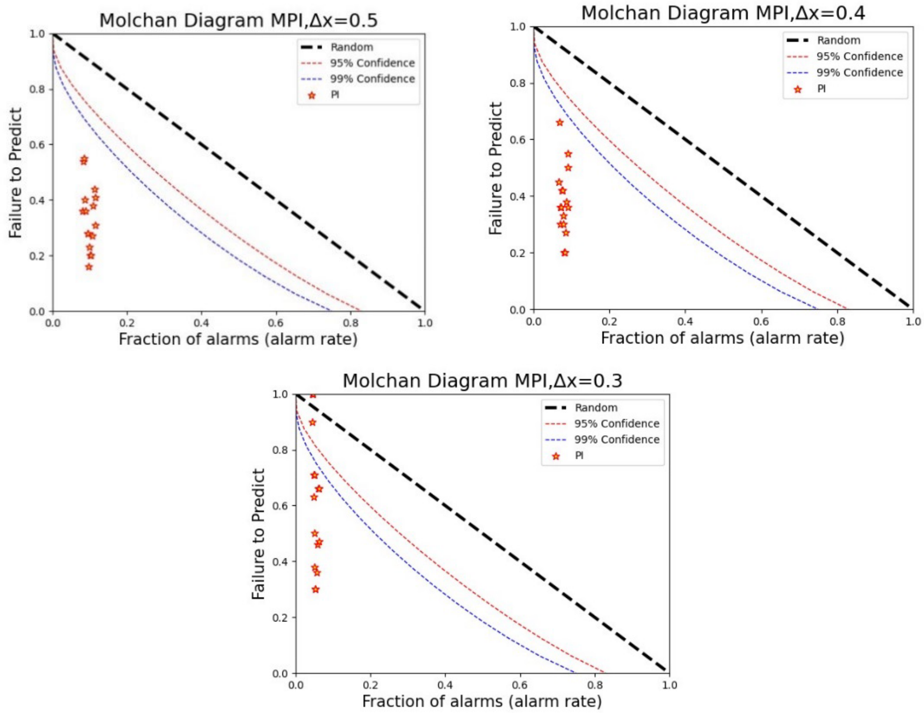
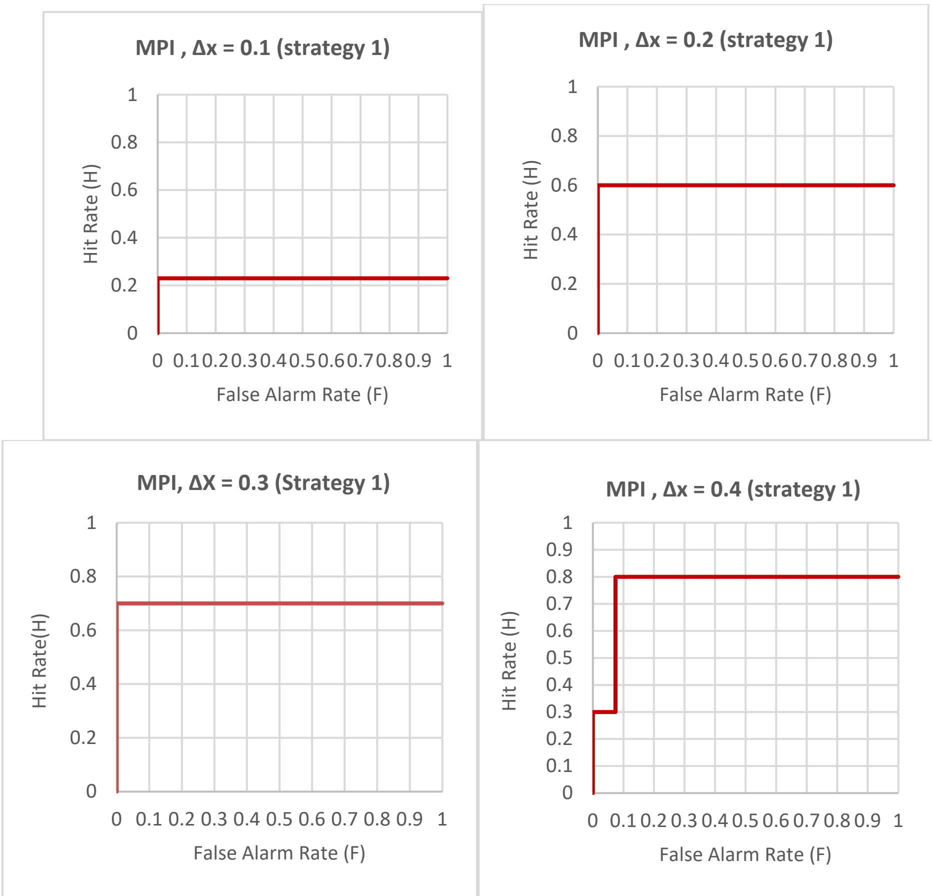


Figure 8. Molchan cart for performance evaluation of MPI (strategy 1) on Δx= 0.1,0.2,0.3,0.4,0.5



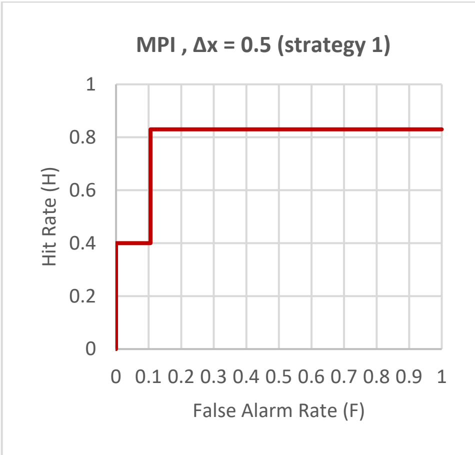


Figure9. Roc plot for performance comparison of MPI (strategy 1) on Δx= 0.1,0.2,0.3,0.4,0.5.

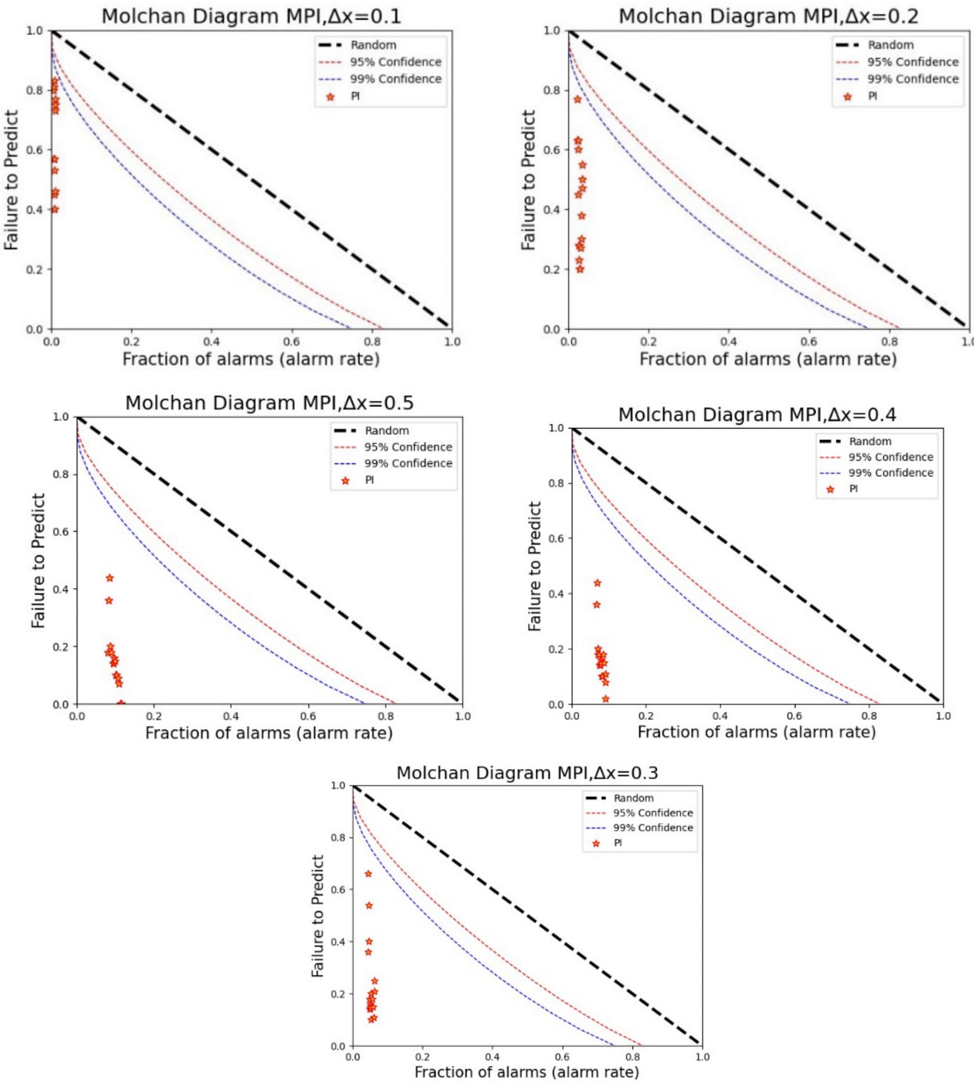


Figure 10. Molchan cart for performance evaluation of MPI (strategy2) on Δx= 0.1,0.2,0.3,0.4,0.5.

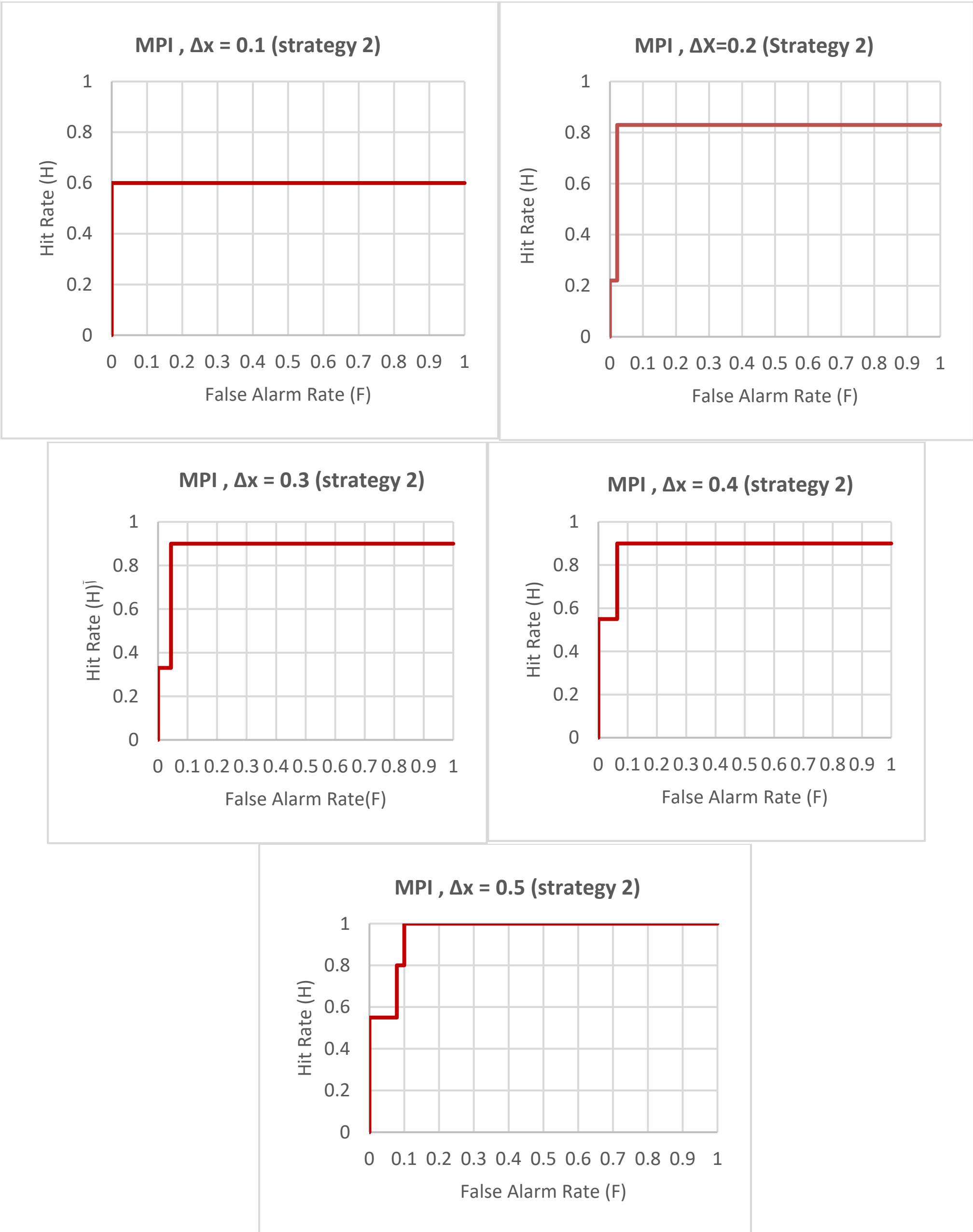


Figure 11. Roc plot for performance comparison of MPI (strategy2) on Δx= 0.1,0.2,0.3,0.4,0.5.

Finally, the Pattern Informatics (PI) method, which identifies regions of anomalous seismic activity toforecast earthquake hotspots, has demonstrated success in predicting earthquake occurrencesin various regions like California and Japan. However, integrating machine learning (ML) algorithms with PI could potentially improve its accuracy and predictive capabilities. The PI method analyzes seismicity fluctuations and identifies "hotspot" regions where earthquakes are likely to occur. For example, a PI-based forecast successfully predicted 16 out of 18 major earthquakes in Southern

California over three years (Holliday, et al., 2005). It relies on historical seismic data and statistical thresholds to detect precursory changes inseismicity.

5 Results

According to evaluation methods, it is determined that in using original PI, forecast results in boxes with dimensions of Δx = 0.4 and Δx = 0.5 degrees exhibit the greatest deviation from random forecasts (The random results thst occur in each binary prediction with a success probability of 50 percent are illustrated in this chart as a half-curve with black dashed points). Consequently, the proposed dimensions for the network configuration of the region to optimize the results with this version for the Zagros region are these dimensions.

Based on the area under the ROC curve (Fig 5), it is evident that the grid with Δx = 0.5 in the initial version of the PI method, which utilizes boxes with dimensions of Δx = 0.5, demonstrates superior results due to the larger area under the curve.

Also, it is evident that in using the modified PI method, the prediction results in boxes with dimensions of Δx = 0.4 and Δx = 0.3 degrees exhibit the greatest deviation from random predictions. Consequently, the proposed dimensions for regional grid spacing to optimize results using the initial version of the PI method, while considering Moor neighborhood (Strategy 2), are these dimensions.

Furthermore, based on the area under the curve in the graphs of Fig 5, since the area under the curve is larger for the grid cells of Δx = 0.3 in the initial version of the PI method with the Moor neighborhood, using boxes with dimensions of Δx = 0.3 yields better results.

Based on the evaluation method (Fig 7), it is evident that in modified PI, the prediction results in boxes with dimensions of Δx = 0.4 and Δx = 0.5 degrees exhibit the greatest deviation from random predictions. Therefore, the proposed dimensions for regional grid spacing to optimize results using the optimized version of the PI method (MPI) with Strategy 1 are these dimensions.

Based on the area under the curve in the graphs of Fig 8, the grid with Δx = 0.5 degrees in the initial version of the PI method, considering the Moor neighborhood, demonstrates better results when using boxes with dimensions of Δx = 0.5.

Based on the evaluation charts, it is observed that the prediction using the Pattern Informatics version method for the seismically active Zagros region, considering the adjacency in the initial version (PI with strategy 2), shows better results with less error.

However, integrating machine learning (ML) algorithms with Pattern Informatics (PI) could potentially improve its accuracy and predictive capabilities. Incorporating machine learning algorithms into the Pattern Informatics method holds significant potential for enhancing earthquake earthquake forecasting accuracy. Machine learning has demonstrate considerable promis in earthquake forecasting by leveraging large datasets and uncovering complex patterns. Unlike the static catalogs used in PI, ML models can continuously learn and adapt as new seismic data becomes available. This integration could combine the strengths of statistical pattern recognition with advanced predictive modeling, offering a more robust tool for seismic risk management. ML algorithms can refine the probability estimates of PI forecasts by analyzing additional features and patterns, providing more accurate predictions with improved results.

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