Journal of Brilliant Engineering 2 (2026) 41097

Brilliant Engineering

journal home: www.acapublishing.com/journals/4/ben

Review Article

Can Earthquakes Announce Their Arrival? : A Short Review

Caglar Ozer[1],*

[1]Atatürk University, Engineering Faculty, Civil Engineering Department, 25140, Erzurum-Türkiye.

Keywords

Earthquake,
Seismic cycle,
Seismic precursors,
Earthquake prediction.

Abstract

Earthquake prediction has been investigated for many decades through multidisciplinary research efforts. Specifically, animal behavioral changes (e.g., ant, dog, frog, horse, mouse, etc.) atmospheric (e.g., cloud movement, thermal infrared, total electron content, very low frequency electromagnetic signals), geochemical (e.g., CO2, radon, and other gases), geodetic (e.g., GPS, GNSS, InSAR), hydrogeological (e.g., groundwater level change), seismic hazard analyses, seismic quiescence period, seismic velocity and seismic velocity ratio, stress analysis, and statistical seismology (e.g., b-value, foreshock distribution, fractal dimension) observations have been extensively applied in studies addressing earthquake prediction. Simultaneously, the development of artificial intelligence and the increase in scientific data, along with the improvement of data evaluation techniques, have further accelerated these studies. This study synthesizes some existing research to highlight the challenges and potential opportunities in short-medium-long term earthquake prediction. Rather than a descriptive approach, this overview presents a structured, concise synthesis of earthquake prediction research by classifying indicators in the literature according to their physical foundations, time-dependent variations within earthquake recurrence intervals, and methodological outcomes. Furthermore, this review is designed primarily for scientists, particularly researchers in earth sciences disciplines, and aims to synthesize the strengths and weaknesses of currently used methodologies, promoting informed evaluation rather than direct deterministic prediction. Recent developments in machine learning and deep learning techniques, particularly those integrating multiple parameters as inputs, are expected to significantly enhance the accuracy of earthquake prediction.

1. Introduction

Earthquake prediction remains among the most difficult challenges in engineering and earth science departments. The complex mechanic of earthquakes is the main obstacle to accurately modeling their formation mechanisms. Differences in geological units, geodynamic processes, crustal movement rate variations, the tectonic unit diversities, difficulties in modeling deep-scale geological units, and the difficulty in determining stress changes with high accuracy are among the main reasons. Therefore, obtaining repeatable and measurable results is still difficult. Despite all these difficulties, literature studies show that there may be some signs preceding earthquakes. These indicators primarily encompass a range of observations, including foreshock distributions, b-values, variations in very low frequency (VLF) signals, changes in seismic velocity and seismic velocity ratios, anomalies detected by Global Positioning System (GPS) and Global Navigation Satellite Systems (GNSS), variations in gases such as radon and CO_2 (carbon dioxide), fluctuations in groundwater levels, observed changes in the atmosphere, ionosphere, and lithosphere, and Ai-based models using machine learning, deep learning, and big data approaches. One of the most systematic structures in this branch is the CSEP (Collaboratory for the Study of Earthquake Predictability). Besides being a platform for international collaboration among scientists, stakeholders, and public institutions, it plays a pioneering role by focusing on developing standards through simulation and developing new earthquake prediction algorithms.

There are two concepts that are frequently confused in society: Earthquake Early Warning (EEW) and Earthquake Prediction (EP). Public media frequently feature claims that earthquakes were predicted seconds in advance. In reality, seismic sensors detect earthquakes occurring at a certain distance from your location are detected by special sensors and low-latency data transfer systems. These systems then warn areas likely to be damaged, primarily due to the difference in the observed arrival times of seismic waves (P- and S-). This process can be summarized as an EEW system [1]. There is no earthquake prediction involved. The fundamental approach is to deliver a warning to an area potentially affected by a destructive event before the destructive seismic waves arrive [2]. This warning time increases as a function of the source–region distance. Depending on your location and the geometry where the EEW sensors are installed, if a destructive earthquake occurs nearby, the P- and S-wave amplitudes may not be sufficiently separated due to the short distance, and therefore the signal may not arrive sufficiently in advance, or it may be limited to a few seconds. Therefore, in EEW systems, the warning comes earlier the further away the destructive earthquake is from you [1]. The biggest advantage of these systems is that they provide time to move to a safe area in region, allowing public institutions and organizations to autonomously shut down systems like electricity and natural gas to prevent potential fires, and giving high-speed trains time to move to a safe position. Earthquake prediction (EP), however, is a very different phenomenon. The aim of EP's is to predict earthquake parameters quickly, including hypocentral location (latitude, longitude, depth), magnitude of an earthquake and origin time by investigating parameters that may directly or indirectly affect the earthquake mechanism before the earthquake occurs. Determining these parameters together is quite difficult. Literature studies have generally focused on spatial predictions and approaches for wide area and time intervals rather than certain location and magnitude.

*Corresponding Author: caglarozer@atauni.edu.tr
Received 14 Dec 2025; Revised 10 Feb 2026; Accepted 10 Feb 2026 https://doi.org/10.36937/ben.2026.41097

Understanding earthquakes requires grasping the theory of elastic rebound. Reid (1911) [3] stated that tectonic plates accumulate stress along tectonic units before an earthquake, and that when this stress exceeds a threshold value depending on the tectonic and geological conditions of the environment, an earthquake occurs, followed by a recovery period during which the affected zone. According to the theory of elastic rebound, there are four important phases: inter-seismic, pre-seismic, co-seismic, and post-seismic. The inter-seismic phase, potential energy begins to accumulate on the fault, and during the pre-seismic phase, deformations begin, reaching a critical level before rupture. The co-seismic phase is when energy is converted into kinetic energy, resulting in the earthquake. The post-seismic phase follows the co-seismic event, wherein, depending on tectonic conditions, the inter-seismic phase is re-begined or the earthquake cycle ends [3,4]. Consequently, earthquakes are characterized as a progressive process rather than a spontaneous event. Therefore, although earthquake prediction studies still have a long way to go, it may be possible to predict earthquakes if the anomalies before the co-seismic period are deterministically established and transformed into a repeatable and measurable form. This is because the inter-seismic and pre-seismic periods, while varying according to tectonic conditions, are generally not a very short period for detecting precursor anomalies.

The aim of this review is not to suggest how to make an earthquake prediction, but rather to offer an overview of the future of earthquake prediction studies using advanced data analytics techniques such as machine learning by examining different precursor parameters reported in areas within the seismic cycle. Another objective of this study is to investigate earthquake prediction parameters and observe which parameters are effective by analyzing representative case studies conducted in different regions.

2. Reviewed methodologies

Hundreds of scientific studies on Earthquake Prediction (EP) have been published and continue to be published. For people living in particularly active tectonic zones, EP is among the most important developments. This study presents a narrative account of articles published between 1996 and 2025, focusing on the specific parameters listed in Table 1. Instead of covering the entire literature, some case studies presenting findings related to certain key parameters have been selected. This study examines earthquake prediction studies related to tectonic earthquakes, excluding types such as volcanic, collapse, eruption, and human-induced earthquakes. The parameters of interest in this review article are presented in six main categories: geophysical and seismological indicators, geodetic and deformation indicators, geochemical and hydrogeological indicators, atmospheric indicators, animal behavior, data integration, big data approaches, and artificial intelligence models. The research was conducted using keywords from the Web of Science, Scopus, and Google Scholar academic search database presented in the parameters/subject column of Table 1. This review article is designed to highlight methodological differences rather than provide a systematic review. Therefore, it aims to provide a synthesis among different parameters, methodologies, and fields of study.

Table 1. Some examples of earthquake prediction studies conducted in different regions. Abbreviations: a: inter-seismic, b: pre-seismic, c: co-seismic, d: post-seismic and r: review study.

Parameters/Topic	Location	Representative Case Studies	Precursor Data
Animal Behavior	Multi-region[1, 2, 3]	Karadeniz (2007)[1] [5]	b
		Mert (2019)[2] [6]	b,r
		Gürbüz and Kutlu (2022)[3] [7]	b
Artificial intelligence and machine learning	Pakistan[1]	Asim et al. (2017)[1] [8]	a,b
	Iran[2]	Yousefzadeh et al. (2021)[2] [9]	a,b
	Multi-region[3, 4, 5]	Bhatia et al. (2023)[3] [10]	a,b
	U.S.A. and Türkiye[6]	Ridzwan and Yusoff (2023)[4] [11]	r
		Ranguelov (2024)[5] [12]	a,b,r
		Yavas et al. (2024)[6] [13]	a,b
b-value and fractal dimension	Türkiye[1, 2]	Öztürk (2014)[1] [14]	a,b
	Japan[3]	Öztürk and Alkan (2022)[2] [15]	a,b
	China[4]	Cao and Gao (2002)[3] [16]	a,b
		Zhang and Zhou (2016)[4] [17]	a,b
Cloud anomalies	Iran[1]	Guo and Wang (2008)[1] [18]	b
Geochemical observations	Japan[1]	Wakita (1996)[1] [19]	b
	Italy[2]	Martinelli et al. (2021)[2] [20]	r
GNSS (Global Navigation Satellite Systems)	Chile[1]	Gürbüz and Koçyiğit (2020)[1] [21]	c,d
Groundwater observations	Japan[1]	Wakita (1996)[1] [19]	b
	China[2]	Chen et al. (2024)[2] [22]	b
Hidden Markov technique	U.S.A.[1]	Yip et al. (2018)[1] [23]	a,b
Ionosphere, atmosphere, lithosphere changes	Multi-region[1]	Akhoondzadeh (2024)[1] [24]	r
Load: Unload Response Ratio (LURR)	U.S.A. and Japan[1]	Yin et al. (2000)[1] [25]	b,r
M8 algorithm	Multi-region[1] (including U.S.A. and Armenia)	Kossobokov (2013)[1] [26]	a,b
Meteorological changes	Türkiye[1]	Uslan and Ulugergerli (2024)[1] [27]	b
Seismic velocities and V_p/V_s ratios	U.S.A.[1]	Whitcomb et al. (1973)[1] [28]	a,b
	Albania[2]	Peci (1995)[2] [29]	a,b
	Türkiye[3]	Ozer (2021)[3] [30]	a,b
Some gas measurements such as Radon and CO_2	Türkiye[1]	Yasin (2020)[1] [31]	b
	Japan[2]	Tsuchiya et al. (2024)[2] [32]	b
	Multi-region[3]	Diaz and Liza (2025)[3] [33]	r
Surface deformations with GPS	U.S.A. and Japan[1]	Gitis et al. (2021)[1] [34]	a,b
Total Electron Content (TEC)	New Zealand[1]	Inyurt et al. (2020)[1] [35]	b
	Türkiye[2]	Bülbül (2024)[2] [36]	b,c,d
Very Low Frequency (VLF)	Haiti, Nepal, Japan[1]	Ulukavak and Demiryege (2019)[1] [37]	b
	Türkiye[2]	Ulaş et al. (2021)[2] [38]	b

2.1. Geophysical and seismological indicators

Foreshock sequences, which are clusters of small-magnitude earthquakes preceding a destructive earthquake, may occasionally provide information on rupture direction and the development of a major event before its onset [39, 40]. The b-value and the Gutenberg-Richter calculations, popular in statistical seismology, provide important clues about stress concentration [14, 15]. Some studies indicate that seismic moment increase in parallel with a decrease in b-values, while others suggest that a low b-value could be a significant indicator of an impending major earthquake [16, 17]. These studies are valuable research in seismic hazard studies [41, 42]. Paleoseismological studies and seismic quiescence periods determined from earthquake recurrence intervals offer important information about the long-term earthquake potential of the tectonic unit [43]. Similarly, some studies have emphasized that seismic velocities and V_p/V_s ratios change before major earthquakes [28-30]. As can be seen, although there have been studies on different geophysical and seismological parameters for many years, the studies conducted are mostly aimed at showing medium and long-term regional stress changes and the state of seismic hazard. Although many geophysical and seismological potential earthquake precursors have been reported, their quantitative performance and data content vary considerably.

2.2. Geodetic and deformation indicators

Deformation changes occurring in the crust during the inter-seismic and pre-seismic periods can be monitored using GPS (velocity and strain) and Interferometric Synthetic Aperture Radar (InSAR). Since tracking creeping and the movement of locked segments is difficult in these analyses, modeling stress accumulation can present greater challenges [21, 34]. At the same time, making deterministic approaches in slow slip events and aseismic creep situations becomes increasingly difficult. It is thought that the ability to detect very small surface deformations before a major earthquake, while not solely crucial, could play a significant role in future earthquake prediction when considered in conjunction with other parameters.

2.3. Geochemical and hydrogeological indicators

Some of the geochemical and hydrogeological precursor indicators reported in the literature exhibit statistically low reproducibility and specific to the study area. Anomalies in groundwater levels and gaseous emissions—specifically radon, CO_2, and SO_2 (sulfur dioxide) are frequently observed prior to major seismic events [31-33]. However, the fundamental problem here, similar to other parameters, is that it cannot be deterministically modelled due to limitations in repeatability. The absence of earthquakes during periods when anomalies occur has been explained by hydrogeological events, noise, and anthropological influences. Therefore, directly linking every geochemical and hydrogeological anomaly to major earthquakes is debatable [20]. A significant disadvantage is that these changes are observed only at certain observation points, despite the possibility of collecting samples directly from or near faults, and similar findings are not obtained at other observation points. The fact that significant changes are observed at some observation points before a major event, while not observed at others, is thought to limit the developments in this topic.

2.4. Electromagnetic and atmospheric indicators

Research exists on changes in TEC (Temperature Equivalent Electron) in the ionosphere layer, associated with events such as gas release or electrical features charging before major earthquakes [35, 36]. Since these anomalies are affected by solar and magnetic storms, it is considered important to separate them from noise and correlate them with tectonic events. Similarly, although LST (thermal infrared) surface temperature changes are investigated as anomalies before major earthquakes, it is difficult to directly correlate them with tectonic events due to their influence by other environmental factors such as humidity and cloud cover [44]. Furthermore, studies reported before some major earthquakes have indicated changes in VLF signals prior to major earthquakes [37, 38]. Studies on advanced approaches to improving earthquake precursor data by removing noise and environmental factors are also considered to be important research topics for the future [38]. Furthermore, studies on clouds have become widespread, and anomalies have been detected before some earthquakes, suggesting that interpreting them in conjunction with other geophysical parameters may be beneficial [18].

2.5. Animal behavior

With the spread of recording devices, the public frequently shares footage of abnormal animal behavior on social media preceding major earthquakes. Scientific studies have also reported abnormal behavior in many animals, including ants, dogs, frogs, horses, and mice before major earthquakes. As with other parameters, the limitations regarding repeatability (the inability to observe similar behaviors before some major earthquakes or the complete lack of reaction during some major earthquakes) have prevented a deterministically of these abnormalities [5-7]. These researches rely on the biological capacity of animals to perceive seismic parameters imperceptible to humans. It is thought that with advancements in neurology, neural signal processing, and artificial intelligence-supported data analysis, more meaningful relationships can be established in this field in the future.

2.6. Data integration, big data approaches, and artificial intelligence models

Training large volumes of data with artificial intelligence-, machine learning-, and deep learning-based systems and investigating meaningful relationships has become a popular topic in addition to statistical seismology studies in recent years. These studies have expanded data catalogs with improvements in both the quality and density of seismic sensors. Developments in ultra-dense seismic networks (large-N arrays) and fiber optic Distributed Acoustic Sensing (DAS) systems could contribute significantly to earthquake prediction in the future. The parallel development of numerous analyses and innovative prediction models will be advantageous in interpreting earthquake data. Especially with the emergence of digital twins over the past several years [45], the accurate characterization of the crust will improve prediction models. The input of the aforementioned parameters into these systems, such as b-values, seismic data, earthquake catalogs, geochemical and hydrogeological data, GNSS data, GPS data, TEC and VLF values, increases the potential for achieving successful results in the future [8-13, 23]. A significant portion of earthquake prediction studies are shifting to this area. The literature is growing on the processing of available parameter data with different techniques and the establishment of meaningful relationships with artificial intelligence-supported studies. However, since the success of this area is directly associated with the improvement and increased accuracy of the fundamental parameters data, proceeding with a multidisciplinary working principle will increase success. Currently, studies based on machine learning and deep learning suggest that models tested in different tectonic environments have low or debatable applicability to other study fields. The main limitation is the non-homogeneous distribution of earthquake distribution data in catalogs, depending on the number and geometry of the seismic stations. With advancements in technology and the relatively lower cost of seismic sensors, earthquake catalogs are improving, and many seismic networks are reaching the capacity to record even very small magnitude events. Furthermore, destructive earthquakes are rarer than small and medium-sized events. This can lead to overfitting machine learning models towards more frequent, low-magnitude events, thus reducing the representational capabilities of the models or approaches in different tectonic environments. This is one of the reasons that makes it difficult to transfer the findings from a regional to a global scale.

3. Case studies on potential parameters observed prior to earthquakes

Wakita (1996) [19], in geochemical and groundwater observations conducted as part of an earthquake prediction project in Japan, noted that anomalies were observed only in sensitive wells, rather than in all wells. It was highlighted the observation of changes in radon gas in some wells before earthquakes and the chemical changes occurring in the groundwater level. The most interesting finding was the report of approximately a 10% increase in chloride ions in 60 bottled drinking water samples taken prior to the 1995 Kobe event (M 7.2). All these findings show that geochemical and groundwater changes occurring underground before destructive earthquakes can be monitored with specially designed systems.

Geller (1997) [46] stated that although earthquake predictions conducted in China, Japan, Russia, and the USA were initially optimistic, they could not be confirmed with data prior to future earthquakes, making predictions difficult in the review study. It was also emphasized that despite testing dozens of parameters such as animal behavior, electromagnetic wave, groundwater level, radon gas, and seismicity repeatable predictions could not be deterministically validated. Although the 1975 Haicheng-China event (M 7.3) was cited as a successful example, Geller (1997) [46] noted that earthquakes still cannot be predicted days or weeks in advance.

Yin et al. (2000) [25] investigated the usability of the LURR (Load/Unload Response Ratio) theory in the EP. It was reported that a ratio value of one indicates elastic behavior, and a value greater than one represents damage accumulation. In case analyses conducted in different tectonic units such as Japan and the USA, it was noted that this value tended to be above one before major earthquakes.

Ileri (2006) [47] emphasized that despite animal behavior, crustal deformations, geochemical changes, groundwater level, seismic activity, and seismic velocity observation generally accepted model has not been reached in earthquake prediction studies.

Karadeniz (2007) [5] reported that some changes could occur in animal and even human behavior before earthquakes, but that it takes time to establish a scientific basis for these changes.

Guo and Wang (2008) [18], using satellite data, reported that two earthquakes with magnitudes of 6.0 and 6.3 occurred 64 and 69 days after anomalous cloud anomalies. In these two events, the location of the earthquake was predicted using anomalous cloud movements, and researchers emphasized that evaluating geophysical, satellite, thermal, and cloud movement data together could increase the success of EP rate.

Kossobokov (2013) [26] emphasized that after the M8 algorithm's success in predicting the 1988 Spitak (M 6.8) and 1989 Loma Prieta (M 7.1) events, the earthquake prediction success of M8 in earthquakes with magnitudes greater than 7.5 has been tested with some examples since the 1990s.

Following the 2009 L'Aquila earthquake (Mw 6.3), seven officials in Italy were sentenced to prison for providing misleading information to the public regarding earthquake prediction [48]. Alexander (2014) [48] conducted a study explaining that those who made statements in the L'Aquila case were tried in their capacity as public officials rather than scientists, and that important lessons can be drawn on how uncertainties should be communicated to the public. This case is a process from which important conclusions should be drawn regarding how and within what limits scientific assessments should be expressed, specifically concerning earthquakes and communication, and how scientific recommendations influence public opinion and policy decision-making processes.

Öztürk (2014) [14] predicted the areas where earthquakes could occur between 2013-2023 in the model developed for Western Anatolia-Türkiye using b-value and fractal dimension analysis. The occurrence of events in Seferihisar (Mw 6.6), Karaburun (Mw 6.2), Sındırgı (Mw 6.1) and Soma (Mw 4.8) within these areas, according to Türkiye Disaster and Emergency Management Authority earthquake catalog data [49], is a remarkable achievement.

Asim et al. (2017) [8] used eight different parameters to identify earthquakes exceeding a magnitude of 5.5 one month in advance in the Hindukush region using different machine learning–based methods, and stated that the highest overall accuracy achieved was 65%.

Yip et al. (2018) [23] analyzed earthquake catalog data (1981-2015) from the southern California region, located near the San Andreas Fault Zone, which has active seismic activity, using a Hidden Markov model and proposed a new earthquake prediction model.

Mert (2019) [6] investigated the relationship between earthquakes and living things and reported that particularly during the L'Aquila earthquake (Mw 6.3), different symptoms were observed, such as abnormal frog behavior, changes in the behavior of red ants, reactions of animals such as dogs, horses, pigs before the earthquake, and an increase in insulin levels in the blood of mice before the L'Aquila earthquake.

Ulukavak and Demiryege (2019) [37] investigated the influence of pre-earthquake variations in the lower ionospheric layers on VLF signals and attempted to interpret VLF signals preceding earthquakes such as the 1995 Kobe (M 7.2), 2010 Haiti (M 7.0), 2015 Nepal earthquakes (M 7.8 and 7.3), and the 2016 offshore Japan earthquake (M 6.9 and 6.1).

Gürbüz and Koçyiğit (2020) [21] investigated the troposphere delays caused by the 2010 Maule (Mw 8.8) and 2015 Illapel (Mw 8.3) events using GNSS data and it was observed significant anomalies during and after the earthquakes (co-seismic and post-seismic period).

Inyurt et al. (2020) [35] investigated the TEC (Total Electron Content) changes in the ionosphere caused by the 2016 New Zealand (Mw 7.8) earthquake and reported that positive anomalies occurred two and four days before the earthquake.

Yasin (2020) [31] investigated the relationship between CO_2-radon gas measurements and earthquakes that occurred in the Karabayır-Eskişehir region over a three-month period.

Ulaş et al. (2021) [38] stated that removing errors in the big data set due to the losses experienced by VLF signals in the ionosphere is an important step. It was announced that developed software capable of performing preliminary analysis of VLF signals to enable more accurate predictions before major earthquakes.

Gitis et al. (2021) [34] reported that it was able to predict 57% of magnitude 6+ earthquakes in Japan and 83% of magnitude 5.5+ earthquakes in California using twelve years of horizontal displacement velocity observations based on GPS-based surface deformations. Although successful results were obtained in two scenarios with different geodynamic characteristics, it was noted that further validation should be considered due to the short observation period, the examination of only two regions, and the limitations to the target earthquakes in this study.

Ozer (2021) [30] stated that P-wave velocity (Vp) and V_p/V_s values could be change at a deep scale after a major earthquake. The low Vp and Vp/Vs values identified in the Bitlis–Zagros Thrust Belt (Türkiye) and certain fault segments could indicate an earthquake elevated earthquake hazard.

Yousefzadeh et al. (2021) [9] developed a fault density variable using four different machine learning techniques and sixteen parameters commonly tested in the literature (including spatial variables that considered to be missing in the literature) to predict earthquakes in Iran over a short period of one week.

Öztürk and Alkan (2022) [15] performed earthquake prediction for the period between 2022 and 2027 in Lake Van-Türkiye using b- and z-values and identified Çaldıran, Gevaş, Muradiye, Özalp and Van city center as areas where potential earthquakes are expected.

Gürbüz and Kutlu (2022) [7] conducted a survey study for the 2020 Sivrice earthquake-Türkiye (Mw 6.8). In this study, it was reported that there was a change in animals, humans, electronic devices, plants and weather conditions approximately 1-2, 24-48, 24-48, 24-120, and 120 hours before the earthquake, respectively.

Bhatia et al. (2023) [10] propose an AI-based prediction system that attempts to process large volumes of seismic data without delay. The results have a high reliability of 95%, and that the integrated use of cloud-based AI techniques can be used for real-time prediction of earthquake magnitude information.

Ridzwan and Yusoff (2023) [11] investigated the effect of different parameters used for different regions of the world in review study examining 31 machine learning-based earthquake prediction studies published between 2017 and 2021. This study concluded that although earthquake predictions are promising, data inconsistencies still exist, and that hybrid models built using region-specific seismic parameters are generally more successful.

Akhoondzadeh (2024) [24] stated that the use of satellite-based data (atmosphere, ionosphere, lithosphere) in earthquake prediction has potential in the future, and that with the increase in the number of satellites launched into space and the development of technology and analysis methods, earthquake predictions with low uncertainty can be reported in the future.

Bülbül (2024) [36] investigated the GNSS-based TEC parameter specifically for the 2023 Kahramanmaraş-Türkiye earthquakes (Mw 7.7 and 7.6). It was reported that the TEC parameter showed an anomaly sixteen days before the Kahramanmaraş earthquakes, and that positive anomalies turned into negative anomalies eight days before the Kahramanmaraş earthquakes. This study emphasized that the TEC value is an important parameter open to improvement in earthquake prediction research.

Chen et al. (2024) [22] analyzed the relationship between groundwater level changes and earthquake prediction using temporal convolutional network based on the magnitude 5.1 earthquake that occurred in Tangshan City, China in 2020, and it is considered to be a promising study for future predictions.

Uslan and Ulugergerli (2024) [27] compared data such as air and seawater temperature, wind and precipitation amounts with earthquakes occurring in the Aegean Sea to investigate the relationship between meteorological changes and earthquakes, and unlike social media, they did not observe a correlation.

Tsuchiya et al. (2024) [32] investigated the 1995 Kobe (Mw 6.9) and 2011 Tohoku-Oki (Mw 9.0) earthquakes using random forest analysis with radon gas data, reporting that the deviation between predicted and observed values surpassed a threshold of three standard deviations. It was emphasized that the importance of random forest analysis and radon measurements in earthquake prediction.

Ranguelov (2024) [12] states, through case studies, that although artificial intelligence techniques may have significant potential in the future, current studies on earthquake prediction using artificial intelligence are being exaggerated.

Yavas et al. (2024) [13] used sixteen different machine-learning techniques to predict earthquakes within a 30-day time window using data from over 23,000 earthquakes around the Los Angeles-USA, and announced the random forest model as the most optimal method with high accuracy. Some issues including lead-time, spatial window definition, data imbalance, overfitting, and domain adaptation have been widely recognized as limiting factors in the robustness and generalizability of machine learning–based earthquake studies [13].

Diaz and Liza (2025) [33] conducted a review study on the relationship between radon gas and earthquake prediction by examining 379 articles published between 1977 and 2025. It was emphasized that the radon gas data is evaluated using techniques such as machine learning, decision tree algorithms, and artificial neural networks, which have developed particularly in recent years, and that this can improve traditional analyses and reveal more meaningful relationships in the future.

A significant acceleration in research, particularly in machine learning and deep learning, is noticeable in the literature. However, over-learning and data imbalance, major challenges in these studies, are among the factors limiting their success. Nevertheless, multidisciplinary studies that consider not only seismological parameters but also other parameters discussed in this study using these techniques will increase success. On the other hand, the quality of earthquake catalogs continues to increase, especially in association with the rise in the number of seismic sensors and improvements in data quality. It is thought that the success of b-value, fractal dimension, and stress analyses will improve proportionally with the increase in the data bank. A similar situation applies to the determination of geodetic parameters with the increase in satellite data and its quality. Studies on animal behavior show that interest in this field has not waned. It is observed that the basis of earthquake prediction studies rests on the ability to detect changes in the inter-seismic and pre-seismic periods. In the future, many variables, likely including different parameters, will focus on understanding the changes before the co-seismic period.

4. Misconceptions, scientific challenges, and future perspectives in earthquake prediction

One of the fundamental challenges encountered in scientific studies on Earthquake Prediction (EP) is the low repeatability of precursor anomalies; while some show striking warning signs before major earthquakes, others show no change at all. The difficulties in purifying the obtained anomalies from noise and reducing them to a specific physical model, and the regional variation in anomaly responses depending on tectonic zones, are other limitations.

There is high public expectation that scientists can predict the location, magnitude, and occurrence time of earthquakes. However, currently, this expectation is far from being met. Nevertheless, scientific studies show that seismic hazard analyses, which can be considered long-term predictions, can calculate the probability of an earthquake and that highly accurate models and approaches are being used. In reality, even if the occurrence of an earthquake could be predicted, the associated damage cannot be entirely mitigated. For example, predicting an earthquake does not change the fact that structures not designed to be earthquake-resistant will be damaged or collapse. In this case, people will still face economic problems due to damage to their places. The primary goal should be to design earthquake-resistant cities rather than predicting earthquakes. In this case, even if an earthquake occurs, the event will not reach disaster proportions, and people will continue their daily lives. The first step is to determine suitable settlement areas by conducting detailed soil investigations. Especially if each stage of the earthquake-soil-structure triad is correctly designed and implemented, the collapse of structures is not expected [50].

Another important point is that successful developments continue in earthquake early warning systems. If earthquakes are a certain distance away from the location, it is possible to give a warning a few tens of seconds before the destructive seismic waves arrive [1]. Errors in EEW systems can sometimes cause trust problems among users. For example, giving a warning as if a small earthquake were a large one, or not giving a warning when an earthquake has occurred, can sometimes lead to problems [51]. On the other hand, as seen in the L'Aquila earthquake, when necessary, warnings are not given, are given incompletely, or are given misleadingly, there can be legal consequences [48]. Modeling the earthquake mechanism to reveal the stress condition and the complex rupture behavior of the tectonic unit, scientific uncertainty, data limitations, and data delays can lead to false warnings or misleading explanations [51]. However, with the development of technology, EEW systems are now widely used. EEW systems were first publicly introduced in Mexico in 1993, and at present, EEW systems are installed in China, Japan, Korea, Romania, Taiwan, Türkiye, and the USA [52]. The EEW system currently installed in China operates through more than 15,000 sensors [53]. Furthermore, systems are in the installation phase in locations such as Chile, Costa Rica, El Salvador, Guatemala, Israel, Italy, Nicaragua, and Switzerland [52].

The increased use of large-N arrays [54] and DAS [55] will lead to a significant increase in data. In the future, the increase in data and sensor numbers will allow for the detection of even small events with high resolution. This will create the opportunity to model tectonic events and stress patterns with higher accuracy. Simultaneously, the widespread use of GPS, GNSS and InSAR techniques and the development of new evaluation techniques can contribute to EP in the future. It is considered that the most important milestone is the ability to create a digital twin by flawlessly modeling the stress conditions in the Earth's crust. Another milestone is that the increase in data volume, and the innovations that machine learning and deep learning-based systems will bring to data evaluation, will allow data obtained with traditional methods in the past to be interpreted and contribute to highly accurate earthquake prediction. The digital twin studies focused on earth sciences is directly related to hardware and computational requirements. In particular, time-dependent monitoring of high-resolution and high-model-volume systems such as DAS and large-N arrays requires a significant technological infrastructure; therefore, advancements in this field can only progress in parallel with technological developments. In summary, it is assessed that there is potential for a significant step forward in earthquake prediction with the development of hybrid models based on field data and artificial intelligence.

5. Synthesis and implications

Many anomalies in various parameters have been reported in the literature before numerous major earthquakes; however, the consistency and repeatability of these anomalies have not yet been deterministically confirmed. That is, a parameter that shows an anomaly in one earthquake may not show any anomaly in another, and a different anomaly may appear in that third earthquake. Therefore, repeatable and provable scientific evidence has not yet been found. Predominantly, earthquake prediction research is retrospective, analyzing data following a seismic event. Studies that analyze data after an earthquake and describe changes in different parameters are common. However, there are only a few studies that assimilate the different parameters observed and make earthquake predictions beforehand (e.g., Haicheng-China earthquake (M 7.3)). Therefore, what science needs now is not so much to say that there are changes in these parameters after major earthquakes, but to be able to make highly accurate earthquake predictions before the earthquake. Successful results are generally thought to be associated with multi-parameter monitoring and site-specific designs. In earthquake prediction studies conducted using artificial intelligence, machine learning, and deep learning-based approaches, data deficiency is considered the biggest obstacle. The number of small and medium-scale magnitude events in the earthquake catalog data is often so large that it may be insufficient for modeling the rupture mechanism of major earthquakes. Another obstacle is that a model applied and tested in one region may not be able to represent areas with different tectonic conditions. At the same time, the fact that earthquake numerical catalogs are not very old and that earthquake records are currently used for a maximum of 100 years (and the years of earthquakes with homogeneous and high-quality solutions mostly correspond to the after 1980s) makes it insufficient for modeling rupture mechanisms with high recurrence intervals. Improvements in this field are possible as the number of earthquake stations increases and their geometry improves, making high-quality earthquake analysis possible. The use of new analysis techniques is also promising. However, it is still thought that time is needed.

The uncertainties in earthquake predictions discussed in the text reinforce engineers' philosophies of performance-based and earthquake-resilient urban planning. Integrating seismic hazard-based designs with earthquake-resistant design is more reasonable than relying solely on deterministic predictions. From this perspective, earthquake prediction research, rather than simply making predictions, indirectly contributes to seismic hazard scenarios and structural static-dynamic designs, which is more logical in minimizing disaster-related problems in the long run. Furthermore, building earthquake-resistant cities should be a primary priority in reducing earthquake damage, as much as predicting earthquakes. By designing earthquake-resilient urban environments, the catastrophic impacts of seismic events can be mitigated, preventing natural hazards from becoming disasters. Historical evidence shows that the most effective reduction in earthquake-related losses is achieved by implementing earthquake-resistant design and building regulations, as can be seen from examples in countries such as Japan and Chile, and that the most reliable strategy for seismic risk reduction is to design earthquake-resistant cities [56-58]. In the 21st century, it is possible to build structures that will not collapse even if they are severely damaged in earthquakes. This depends on advanced engineering and site-specific research that models the soil with high accuracy, resulting in structures that correctly design the earthquake-soil-structure relationship. Therefore, earthquake prediction, even if achievable, cannot be considered a standalone or long-term solution.

Nomenclature

AI: Artificial intelligence

CO_2: Carbon dioxide

DAS: Distributed acoustic sensing

EEW: Earthquake early warning

EP: Earthquake prediction

GNSS: Global navigation satellite systems

GPS: Global positioning system

InSAR: Interferometric synthetic aperture radar

Large-N arrays: Ultra-dense seismic networks

LST: Thermal infrared

LURR: Load/Unload response ratio

M: Magnitude

SO_2: Sulfur dioxide

TEC: Total electron content

VLF: Very low frequency

V_P: P- wave velocity

V_p/V_s: Seismic velocity ratio

Declaration of Conflict of Interests

The author declares that there is no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The author used the OpenAI/ChatGPT tool for language editing and grammar improvements.

References

[1.] Suarez, G., The seismic early warning system of Mexico (SASMEX): A retrospective view and future challenges. Frontiers in Earth Science 10 (2022) 827236.

[2.] Lux, A.I., Smith, D., Böse, M., McGuire, J.J., Saunders, J.K., Huynh,M., ... & Toomey, D., Status and performance of the ShakeAlert earthquake early warning system: 2019-2023. Bulletin of the Seismological Society of America 114(6) (2024) 3041-3062.

[3.] Reid, H.F., The elastic rebound theory of earthquakes. University of California Publications- Bulletin of the Department of Geological Sciences 6 (1911) 413-444.

[4.] Dönmez, E., Tiryakioğlu, İ., Monitoring of tectonics movements of gediz fault with GNSS observations. Afyon Kocatepe University Journal of Science and Engineering 18(3) (2018) 1110-1117 (in Turkish).

[5.] Karadeniz, A., Earthquake and abnormal animal behaviours. Atatürk University Journal of Veterinary Sciences 2(3) (2007) 99-102 (in Turkish).

[6.] Mert, N., Earthquakes and their effects on living organisms. Eurasian Journal of Health Sciences 2(4) (2019) 137-144 (in Turkish).

[7.] Gürbüz, S., Kutlu, Y.A., Precursors of the Elazig-Sivrice earthquake (January 24th, 2020). Turk Deprem Arastirma Dergisi 4(2) (2022) 246-260 (in Turkish).

[8.] Asim, K.M., Martinez-Alvarez, F., Basit, A., Iqbal, T., Earthquake magnitude prediction in Hindukush region using machine learning techniques. Natural Hazards 85(1) (2017) 471-486.

[9.] Yousefzadeh, M., Hosseini, S.A., Farnaghi, M., Spatiotemporally explicit earthquake prediction using deep neural network. Soil Dynamics and Earthquake Engineering 144 (2021) 106663.

[10.] Bhatia, M., Ahanger, T.A., Manocha, A., Artificial intelligence based real-time earthquake prediction. Engineering Applications of Artificial Intelligence 120 (2023) 105856.

[11.] Ridzwan, N.S.M., Yusoff, S.H.M., Machine learning for earthquake prediction: A review (2017-2021). Earth Science Informatics 16(2) (2023) 1133-1149.

[12.] Ranguelov, B., New trends in earthquake prediction-A case study of AI performance. Earthquake 3(1) (2024) 8254.

[13.] Yavas, C.E., Chen, L., Kadlec, C., Ji, Y., Improving earthquake prediction accuracy in Los Angeles with machine learning. Scientific Reports 14(1) (2024) 24440.

[14.] Öztürk, S., A study on earthquake statistics and the forecasting for the intermediate-term locations of possible strong earthquakes for the Western Anatolian Region of Turkey. Gümüşhane University Journal of Science and Technology 4(1) (2014) 75-93 (in Turkish).

[15.] Öztürk, S., Alkan, H., A statistical analysis and evaluation on the earthquake forecasting and hazard for Lake Van and its adjacent area (Türkiye). Turk Deprem Arastirma Dergisi 4(2) (2022) 191-209 (in Turkish).

[16.] Cao, A., & Gao, S. S. (2002). Temporal variation of seismic b-values beneath northeastern Japan island arc. Geophysical research letters, 29(9), 48-1.

[17.] Zhang, S., & Zhou, S. (2016). Spatial and temporal variation of b-values in southwest China. Pure and Applied Geophysics, 173(1), 85-96.

[18.] Guo, G., Wang, B., Cloud anomaly before Iran earthquake. International Journal of Remote Sensing 29(7) (2008) 1921-1928.

[19.] Wakita, H., Geochemical challenge to earthquake prediction. Proceedings of the National Academy of Sciences 93(9) (1996) 3781-3786.

[20.] Martinelli, G., Ciolini, R., Facca, G., Fazio, F., Gherardi, F., Heinicke, J., Pierotti, L., Tectonic-related geochemical and hydrological anomalies in Italy during the last fifty years. Minerals 11(2) (2021) 107.

[21.] Gürbüz, G., Koçyiğit, K., Relation between earthquake and the troposphere: Chile example. Afyon Kocatepe University Journal of Science and Engineering 20(6) (2020) 1014-1023 (in Turkish).

[22.] Chen, X., Yang, L., Liao, X., Zhao, H., Wang, S., Groundwater level prediction and earthquake precursor anomaly analysis based on TCN-LSTM-attention network. IEEE Access 12 (2024) 176696-176718.

[23.] Yip, C.F., Ng, W.L., Yau, C.Y., A hidden Markov model for earthquake prediction. Stochastic Environmental Research and Risk Assessment 32(5) (2018) 1415-1434.

[24.] Akhoondzadeh, M., Earthquake prediction using satellite data: Advances and ahead challenges. Advances in Space Research 74(8) (2024) 3539-3555.

[25.] Yin, X.C., Wang, Y.C., Peng, K.Y., Bai, Y.L., Wang, H.T., Yin, X.F., Development of a new approach to earthquake prediction: Load/Unload Response Ratio (LURR) theory. Pure and Applied Geophysics 157(11) (2000) 2365-2383.

[26.] Kossobokov, V.G., Earthquake prediction: 20 years of global experiment. Natural Hazards 69(2) (2013) 1155-1177.

[27.] Uslan, E., Ulugergerli, E., Can an earthquake be predicted using meteorological data?. Turk Deprem Arastirma Dergisi 6(2) (2024) 452-470 (in Turkish).

[28.] Whitcomb, J.H., Garmany, J.D., Anderson, D.L., Earthquake prediction: Variation of seismic velocities before the San Francisco earthquake. Science 180(4086) (1973) 632-635.

[29.] Peci, V., The behaviour of some precursors before some strong earthquakes occurred in Albania and surrounding areas. 3rd National Earthquake Engineering Conference (1995).

[30.] Ozer, C., 4-D tomographic change of Vp and Vp/Vs structure before destructive earthquakes: A case study of the Sivrice-Elazığ earthquake (mw= 6.8), Eastern Turkey. Natural Hazards 108(2) (2021) 1901-1917.

[31.] Yasin, D., Investigation of the relationship between the change in radon and carbon dioxide soil gas concentrations and earthquakes: Karabayır (Eskisehir) case study. Afyon Kocatepe University Journal of Science and Engineering 20(3) (2020) 518-527 (in Turkish).

[32.] Tsuchiya, M., Nagahama, H., Muto, J., Hirano, M., Yasuoka, Y., Detection of atmospheric radon concentration anomalies and their potential for earthquake prediction using Random Forest analysis. Scientific Reports 14(1) (2024) 11626.

[33.] Diaz, F., Liza, R., Radon anomalies and earthquake prediction: trends and research hotspots in the scientific literature. Geosciences 15(8) (2025) 283.

[34.] Gitis, V., Derendyaev, A., Petrov, K., Analyzing the performance of GPS data for earthquake prediction. Remote sensing 13(9) (2021) 1842.

[35.] Inyurt, S., Mekik, Ç., Yıldırım, Ö., Developing a new approach for determination of possible ionospheric changes caused by earthquake. Journal of Geomatics 5(2) (2020) 127-133 (in Turkish).

[36.] Bülbül, S., Investigation of TEC anomalies possibly caused by the 6 February 2023 Kahramanmaraş (Turkey) earthquakes with space weather conditions. Bulletin of Geophysics and Oceanography 65(4) (2024) 513-534.

[37.] Ulukavak, M., Demiryege, İ., Investigation of M≥6.0+ earthquake precursors with Very Low Frequency (VLF) radio receivers. GSI Journals Serie C: Advancements in Information Sciences and Technologies 2(1) (2019) 23-39 (in Turkish).

[38.] Ulaş, M., Balık, H.H., Ata, F., Autonomous VLF signal debug algorithm for leading earthquake precursors analysis. Firat University Journal of Science 33(1) (2021) 93-102 (in Turkish).

[39.] Eyidoğan, H., Investigation of the temporal and spatial properties of earthquake activity and Gutenberg-Richter parameters in the vicinity of Manisa Akhisar. Turk Deprem Arastirma Dergisi 2(2) (2020) 138-159 (in Turkish).

[40.] Kalafat, D., Earthquake patterns in Türkiye. Bulletin of the Earth Sciences Application and Research Centre of Hacettepe University 44(3) (2023) 222-233 (in Turkish).

[41.] Bayrak, E., Yılmaz, Ş., Softa, M., Türker, T., Bayrak, Y., Earthquake hazard analysis for East Anatolian fault zone, Turkey. Natural Hazards 76(2) (2015) 1063-1077.

[42.] Bayrak, E., Yılmaz, Ş., & Bayrak, Y. (2017). Temporal and spatial variations of Gutenberg-Richter parameter and fractal dimension in Western Anatolia, Turkey. Journal of Asian Earth Sciences, 138, 1-11.

[43.] Gürboğa, Ş., Gökçe, O., Paleoseismological catalog of Pre-2012 trench studies on the active faults in Turkey. Bulletin of Mineral Research and Exploration 159 (2019) 65-89 (in Turkish).

[44.] Saraf, A.K., Rawat, V., Banerjee, P., Choudhury, S., Panda, S.K., Dasgupta, S., Das, J.D., Satellite detection of earthquake thermal infrared precursors in Iran. Natural Hazards 47(1) (2008) 119-135.

[45.] Wang, Y., Wang, L., Han, W., Yan, J., Digital twin of earth: A novel information framework for managing a sustainable earth. The Innovation Geoscience 2(4) (2024) 100092-1.

[46.] Geller, R.J., Earthquake prediction: a critical review. Geophysical Journal International 131(3) (1997) 425-450.

[47.] Ileri, İ. Can an earthquake give warning signs?. Mavi Gezegen 13 (2006) 19-24 (in Turkish).

[48.] Alexander, D.E., Communicating earthquake risk to the public: the trial of the "L'Aquila Seven". Natural Hazards 72(2) (2014) 1159-1173.

[49.] AFAD. (2025). The online earthquake catalog of Ministry of Interior Disaster and Emergency Management Presidency of Türkiye. http://www.deprem.gov.tr. Accessed: 01 Sept 2025.

[50.] Genç, A.F., Atmaca, E.E., Guenaydin, M., Altunişik, A.C., Sevim, B., Evaluation of soil structure interaction effects on structural performance of historical masonry buildings considering earthquake input models. Structures 54 (2023) 869-889.

[51.] Minson, S.E., Baltay, A.S., Cochran, E.S., Hanks, T.C., Page, M.T., McBride, S.K., ... & Meier, M. A., The limits of earthquake early warning accuracy and best alerting strategy. Scientific reports 9(1) (2019) 2478.

[52.] Dallo, I., Marti, M., Clinton, J., Böse, M., Massin, F., Zaugg, S., Earthquake early warning in countries where damaging earthquakes only occur every 50 to 150 years-The societal perspective. International Journal of Disaster Risk Reduction 83 (2022) 103441.

[53.] Wang, W., Xie, J., Li, X., Usability of records by China earthquake early warning network for ground motion modeling. Soil Dynamics and Earthquake Engineering 196 (2025) 109497.

[54.] Li, Z., Peng, Z., Hollis, D., Zhu, L., McClellan, J., High-resolution seismic event detection using local similarity for Large-N arrays. Scientific reports 8(1) (2018) 1646.

[55.] Taha, B.A., Addie, A.J., Haider, A.J., Osman, S.A., Ramli, M.Z., Arsad, N., A review of seismic detection using fiber optic distributed acoustic sensing: from telecommunication cables to earthquake sensors. Natural Hazards 121 (2025) 13927-13959.

[56.] Takagi, J., Wada, A., Recent earthquakes and the need for a new philosophy for earthquake-resistant design. Soil Dynamics and Earthquake Engineering 119 (2019) 499-507.

[57.] Anant, K.M., Charpe, P.S., Analysis of seismic forces for earthquake-resistant constructions. International conference on emerging global trends in engineering and technology (2022) 145-163. Singapore: Springer Nature Singapore.

[58.] Lagos, R., Lafontaine, M., Bonelli, P., Boroschek, R., Guendelman, T., Massone, L. M., ... & Yanez, F., The quest for resilience: The Chilean practice of seismic design for reinforced concrete buildings. Earthquake Spectra 37(1) (2021) 26-45.

How to Cite This Article

Ozer, C., Can Earthquakes Announce Their Arrival? : A Short Review, Brilliant Engineering, 2(2026), 41097.
https://doi.org/10.36937/ben.2026.41097