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A review on clustering algorithms for spatiotemporal seismicity analysis

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Abstract
Spatiotemporal seismicity analysis has been conducted for a long time, yet significant effort is still needed to mitigate the adverse effects of earthquakes. Seismicity analysis also encompasses fundamental research into seismic patterns, for understanding the frequency, magnitude, temporal and spatial distribution of seismic events. Over the past few decades, it has been carried out through empirical relations, physics-based approaches, stochastic modeling, various machine learning algorithms, and deep learning algorithms for any given seismically active region. Clustering is an essential aspect of seismicity analysis, making it more complex, difficult, and challenging due to significant deviation from the stochastic phenomenon. In this paper, a comprehensive review of all potential data-driven earthquake clustering algorithms, models, and mechanisms are encapsulated for a variety of applications in seismology. The paper also describes the importance of an earthquake catalog with a short review of the fundamental empirical laws frequently used in statistical seismology. This paper also highlights the problem of seismicity declustering and reviews all the available algorithms to deal with it.

Keywords Spatiotemporal seismicity · Earthquake catalogs · Clustering · Seismicity declustering · Prediction · Early warning systems

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1 Introduction

Earthquakes are one of the most hazardous natural disasters caused by the shaking of the earth's surface, resulting in a sudden release of energy in all directions in the form of seismic waves. Strong earthquakes can strike without warning, causing extensive infrastructure damage, loss of life, and economic losses within seconds. However, there is a debate about the potential role of foreshocks in improving the forecasting of large earthquakes. Since 1901, the worldwide occurrence of earthquakes with a magnitude greater than or equal to 6 is shown in Fig. 1. Here, the color bar represents the depth variation in available data. Earthquake occurrences in each decade since 1901 are illustrated in Fig. 2 by taking different magnitude ranges. A showcase of strong earthquakes (M8+) worldwide in each decade is also depicted in Fig. 2 by purple color bar chart. It shows that more than 10 strong earthquakes occurred for two consecutive decades, 2001-2010 and 2011-2020, with an ongoing present decade. Due to this, around the 20th century, there was a significant hike in the number of overall earthquakes, as evident from Fig. 2 (bottom bar chart with blue color). It is due to the improvement in the technology for finding, locating, and recording the source of earthquakes (USGS 2024). This sudden rise in seismic activities and ease of data availability motivates many seismologists to improve existing methods, tools, and techniques to mitigate the post-effects by taking precautionary measures.

A close examination and strong evidence about spatial and temporal distributions of earthquakes in a seismically active region reveal significant deviations from the randomly occurring Poisson process (Kagan and Jackson 1991). The occurrence of events exhibits a strong correlation, especially in space and time, with a tendency to form clustering patterns (Jagla and Kolton 2010). The formed clustering structures in the spatiotemporal domain can have elongated and sometimes irregularly shaped patterns and varying densities with a dependency on earthquake magnitudes (Georgoulas et al. 2013; Bountzis et al. 2021; Yamagishi et al. 2021). This clustering behavior enhances the seismic rate drastically around

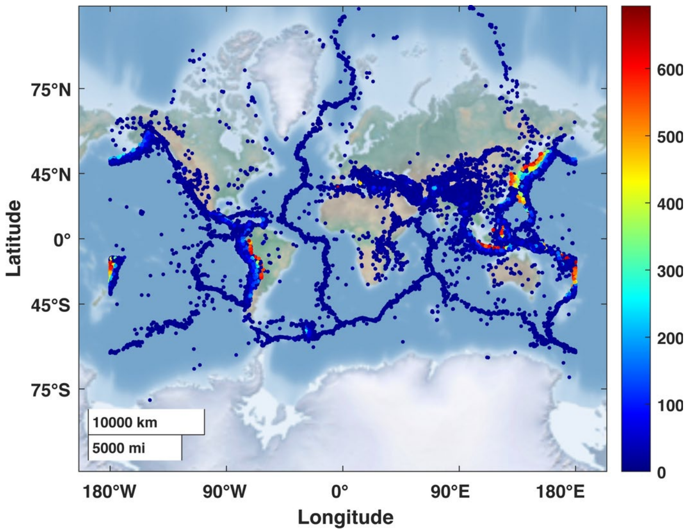


Fig. 1 World-wide earthquakes (6.0+ Mw) occurred during 1901–2023 with depth (in km) variation shown in different colors

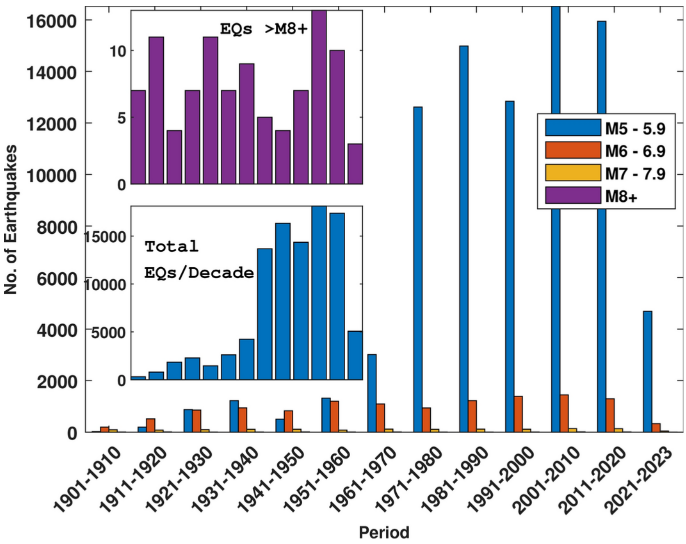


Fig. 2 The main plot shows the number of earthquakes in each decade since 1901, with different magnitude ranges shown. The insets highlight the number of strong quakes (shown in purple) and the total number of earthquakes that occurred (shown in blue) in each decade (bin size)

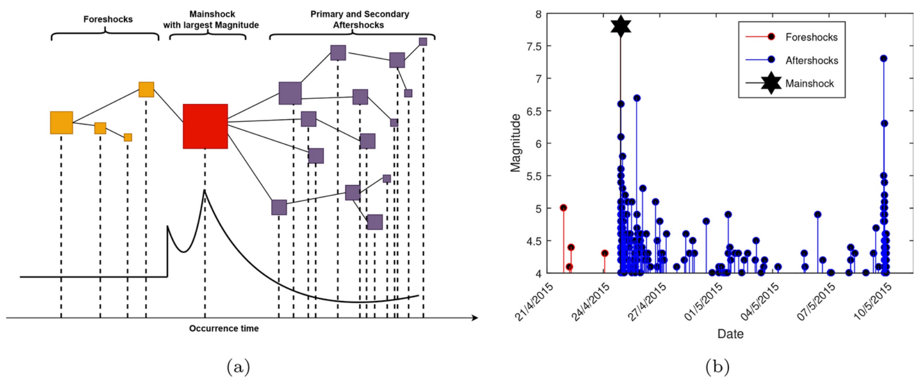


Fig. 3 **a** Categories of events based on their occurrence time and relative magnitude. **b** Foreshock (in red) and aftershock (in blue) sequences before and after the occurrence of strong mainshock on April 26, 2015, at Gorkha in Nepal

strong earthquakes in a region, with closeness in time [temporal clustering (Kenner and Simons 2005; Chéry et al. 2001)], and along the earthquake faults [spatial clustering (Kosobokov and Mazhkenov 1992; Telesca et al. 2015a)].

This inherent clustering pattern is defined in terms of the *foreshocks/early-aftershocks* and *aftershock* sequences, which are triggered in a chain effect fashion before and after the large event referred to as *mainshock* as illustrated in Fig. 3a. Their occurrences do not show random behavior but have correlated consecutive triggering effects from interconnected underlying faults in a region. Both types of sequences are related to the larger earthquakes (mainshock) and occur in different phases of the earthquake sequence. It is reflected in

Fig. 3b, which shows the real-world example of the fore-main-aftershock sequences at the time of the Gorkha earthquake in Nepal on April 26, 2015, which occurred in the world's most seismically active continental Himalaya region. The *foreshock* has public attention due to its importance as a precursor to a mainshock, and researchers are curious to know the chances of a larger descriptive earthquake immediately after the occurrence of moderate foreshock activities (Seif et al. 2019). As per the report, the forecast of the Haicheng earthquake (1975 February 4, 7.3M, mainshock) was made based on foreshock sequences (Jones et al. 1982). Zaccagnino et al. (2024) found the grouping of foreshocks as clustered in the spatial domain before large earthquakes; they do not predict mainshocks effectively. However, their study in Southern California revealed that foreshock clusters are not used as a source of information by analyzing clusters for short-term earthquake prediction.

Aftershock sequences belong to the same family as foreshocks, and they contain many small events (triggered by the same, largest, and most significant earthquake; mainshock), and their temporal decay is described by empirical laws. In the worldwide catalog, aftershocks contribute around 30–40 percent to the total number of earthquakes. Thus, their reliable locations are essential for finding significant information about rupture processes, estimating the fault rupture area, defining scaling relations between small and large earthquakes, etc. Recently, mainshock-aftershock sequences have been utilized for predicting the location of aftershocks using deep learning method (DeVries et al. 2018). Similarly, the *earthquake* swarm is another family that has a cluster of moderate earthquakes with occurrence over hours to days without a distinct mainshock. They are generally observed in volcanic environments, hydro-thermal systems, and other active geothermal areas (Peng et al. 2021b).

Apart from these, natural, low-magnitude earthquakes occurred in a specific region over a long period, unrelated to any immediate, strong tectonic events. These events are considered as *background* due to the ongoing motion of tectonic plates, stress accumulation along faults, and other geological and tectonic activities. Background seismicity-related studies and research are useful in establishing baseline levels of earthquake activity in a region. Furthermore, it helps in seismic hazard analysis and a better understanding of the dynamics of the earth's crust.

In the spatiotemporal domain, the distribution of earthquake occurrences and its relevance with clustering patterns are shown by histograms in Fig. 4. It illustrates several events that occurred quarterly, such as the magnitude and depth distributions of earthquakes from 2001 to 2024 in the Himalaya. This region has frequent strong earthquakes with Magnitude > 7, such as in 2001 (Bhuj EQ with 7.7M and Kunlun EQ with 7.8M), in 2002 (Hindu Kush EQ with 7.4M), in 2005 (Kashmir EQ with 7.6M), 2008 (Xinjiang EQ with 7.2M), in 2015 (Gorkha EQ with 7.8M and Pokhara EQ with 7.3M) and in 2021 (Yangbi with 7.3M). Mostly, there is a hike in the number of events during these times, as evident from Fig. 4 with the presence of peaks. This is due to the occurrence of foreshock/aftershock sequences corresponding to mainshock with some background activity. Similarly, non-uniform depth distribution in the entire region and log-linear frequency magnitude distribution of earthquake are revealed in Fig. 4.

Similarly, in Fig. 5a, the bunches of events are visible at the place where a strong earthquake (shown by black hexagrams) has occurred. The black hexagrams represent strong earthquakes that produced significant damage and loss of life. Figure 5b provides a scattered view of the catalog, showing their location and time. Highly dense events with more

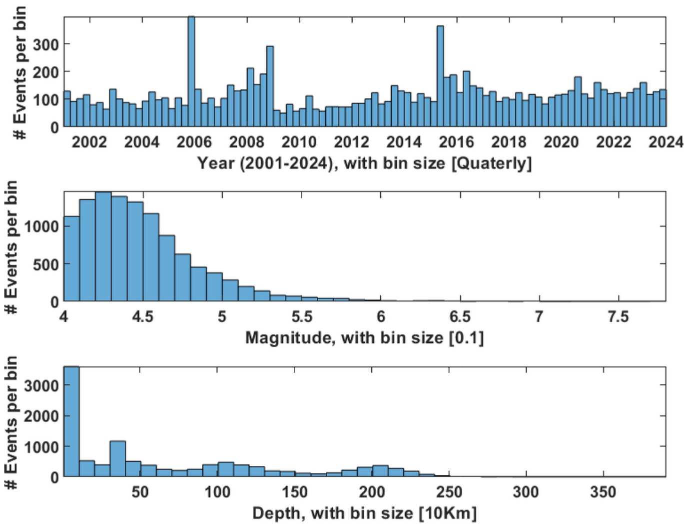


Fig. 4 Distribution of events every three months from the year 2001 to 2024, revealing the hike especially in the years 2005, 2008, and 2015 due to strong mainshock. Other histograms present the magnitude and the depth frequency distributions, respectively, derived for the Himalayan region. Here, it must be noted that the increased number of intermediate-magnitude ($4 < M < 4.5$) events, with the majority of events being shallow (Depth < 10 km) in the region

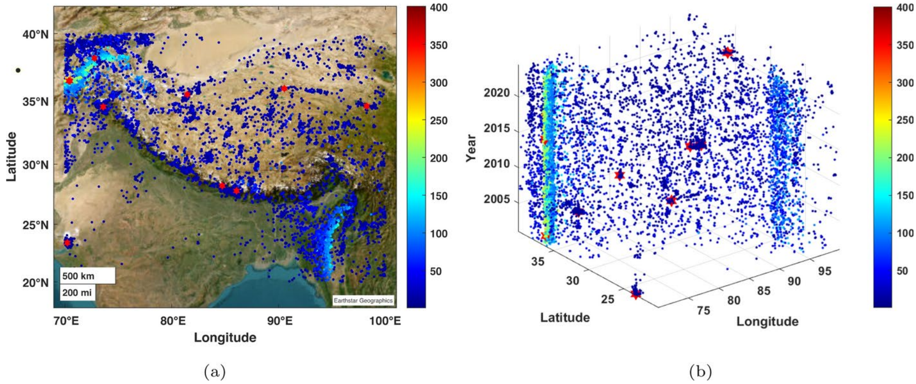


Fig. 5 **a** Distribution of earthquake epicenters, **b** Scatter plot of earthquake epicenters with reference to their occurrence time during 2001–2024 in Himalaya. Here, red hexagrams represent the strong quakes (Magnitude ≥ 7.0) with depth variations shown by different colors

concentration at the time of strong earthquake indicate the clustering pattern relevant to the main shock in the spatiotemporal domain. Depth homogeneity and their correlation among the events are also evident from both figures. The depth variations are shown by different colors in the color bar. Here, earthquake records are obtained from the USGS website (USGS 2024). The definitions and patterns of seismic activities are inherently complex and depend significantly on the selection criteria for the mainshock, as well as the geological and physical characteristics of the geographic region under study. These considerations can provide valuable insights into the geological structure of the region and the mechanisms driving seismic events. Furthermore, they can be utilized to investigate the spatiotemporal relationships of seismic activities and their dependencies on factors such as magnitude, depth, tectonic settings, and other geological and seismological parameters.

In such a scenario, clustering algorithms provide a method to identify the grouping of events based on their spatial proximity, closeness in the time domain (Kumar and Sengupta 2024; Wen et al. 2023), and its correlation with other earthquake parameters. Spatiotemporal seismicity analysis through clustering is helpful to identify patterns, relationships, and trends in earthquake occurrences, providing valuable insights for earthquake prediction (Zaccagnino et al. 2023a), hazard assessment (Wang et al. 2023), aftershock forecasting (Liu et al. 2023b; Hardebeck et al. 2024), earthquake nowcasting (Baughman et al. 2023), foreshock detection (Nomura and Ogata 2023), seismotectonic studies (Bulut et al. 2012), and earthquake early warning systems (EEWs) (Kolivand et al. 2024). In the past, the majority of clustering algorithms/models are developed for the following purposes:

- *Identifying Seismic Sequences*: Seismic sequences are identified that are temporally and spatially related such as aftershocks, earthquake swarms, and foreshocks (Gentili et al. 2024; Im and Avouac 2023).
- *Detecting fault zones*: Clustering in the spatial domain is applied that often correlates with known geological structures like subduction zones, mid-ocean ridges, and plate boundaries (Goebel et al. 2023).
- *Accessing periodicity and multi-fractal behavior:* Temporal distributions and access periodicities might reveal patterns in aftershock decay rates or seismic recurrence intervals. Time-based clustering can be important for analyzing the dynamics of stress accumulation and release over time (Ida 2024; Babu et al. 2023)
- *Magnitude Clustering:* Grouping of events according to their size is useful to investigate stress transfer between large and small events and to define scaling relations for knowing distribution within a fault system (Georgoulas et al. 2013; Xiong et al. 2023; Sabbeth et al. 2023).
- *Seismic Hazard Assessment:* Clustering earthquakes in terms of their magnitude, location, and temporal proximity, it is possible to identify areas of higher seismic hazard (Zaccagnino et al. 2023b). It might help to indicate a higher likelihood of future large events in that region.
- *Understanding triggered seismicity:* Clustering is also applied to understand triggered seismicity, where a strong earthquake induces additional events in the surrounding region. By identifying clusters of earthquakes that occur shortly after a significant event, researchers can better understand the processes behind seismic triggering, such as stress transfer from a large earthquake, fluid migration due to faulting, or fault zone changes (Glasgow et al. 2023; Taroni et al. 2024).
- *Seismic Pattern Recognition* In modern earthquake studies, machine learning (ML) methods are increasingly being used to automate the process of identifying seismic sequences or complex, nonlinear patterns that may not be apparent through traditional methods (Zhao et al. 2024; Bhujang and Kotagi 2023).
- *Improving Earthquake Forecasting Models* Clustering techniques are also helpful in improving forecasting models such as the ETAS (Epidemic-Type Aftershock Sequence) model. It helps to simulate aftershock sequences based on clustering principles (Petrillo

and Lippiello 2023; Zhan et al. 2024; Kwon et al. 2023).

Modeling and simulation of earthquake occurrences have been primary goals of research in seismology for the last few decades. It helps to understand its dynamic behavior and characterize the overall seismicity of a particular region (Console et al. 2023). Generally, this is carried out by considering the historical information about the event's hypocenter locations, occurrence time, event's magnitude, and other geological and seismological information available for a region of interest. This data-driven analysis of the seismicity using multiple information for a prone region cannot be carried out by individual earthquakes. Mostly, it is based on the group of events that occur in space and time over long distances with different magnitude scales (Zechar et al. 2011) in a particular region. Still, it is an open debate whether to develop statistical approaches for seismicity modeling or to develop physical mechanisms for similar purposes. Although it is difficult to build a mathematical model based solely on the given data without considering or understanding the underlying physics of earthquake dynamics (Stein and Wysession 2009)

This paper provides a detailed review of spatiotemporal seismicity in a clustering framework summarizing related laws, availability of data, algorithms, potential applications, and associated challenges. In brief, the following are the important aspects of the paper:

- Encompasses insights from various studies, shedding light on various clustering approaches especially suited for spatiotemporal seismicity analysis.
- Highlights detailed information about catalogs with a spotlight on their types, availability, accessibility, generation mechanism, challenges, and limitations.
- Lists all fundamental empirical laws that are directly/indirectly related to the spatiotemporal aspects of seismicity and inherently affect the clustering outcomes of any active region.
- Focuses on 'Seismicity Declustering' and addresses the state-of-the-art declustering methods in addition to recently reported algorithms with their advantages and disadvantages.
- Lastly, it emphasizes the role of Artificial Intelligence in uplifting seismicity analysis with applications, challenges, and future objectives.

The subsequent sections of the paper are organized as follows. Section 2 provides detailed information about the earthquake catalogs in terms of types, preparation mechanisms, availability, accessibility, challenges, and limitations. Fundamental empirical laws related to spatiotemporal seismicity are narrated in Sect. 3. A comprehensive review of various clustering algorithms for spatiotemporal seismicity analysis is presented in Sect. 4. Section 5 highlights seismicity declustering with state-of-the-art declustering algorithms and recently reported approaches with their advantages and disadvantages. Section 6 summarizes the role of Artificial Intelligence in the analysis of spatiotemporal seismicity, applications, and challenges followed by a conclusion and future scope in Sect. 7.

2 Data sources for clustering in spatiotemporal seismicity analysis

Long-term and short-term clustering characteristics are based on historical and instrumental earthquake data that accurately provide a non-subjective judgment about hazard studies in a seismically active region (Huang et al. 2022). Nowadays, instead of subjective interpretations based on geological and seismotectonic information, machine learning approaches provide more accurate results by identifying patterns from a huge amount of historical availability of data. However, comprehensive and updated earthquake records are the most important source of information for developing a clustering model that can improve:

- Understanding the relationship between seismic activity and tectonic processes.
- Predicting aftershock sequences to minimize risks after strong earthquakes.
- Enhancing the effectiveness of real-time earthquake alert systems.
- Identifying regions at higher risk of seismic activity for urban planning and infrastructure development.

The accuracy of the clustering approaches depends on data availability and its quality and completeness. The reliable, complete, and accurate event information provides a justified spatiotemporal distribution of earthquake sequences with insights into their spatial and temporal statistics. Further, it can be utilized to investigate triggering mechanisms after acquiring a sufficiently long history of updated earthquake records of a region of interest.

2.1 Catalogs availability

Earthquake catalog contains the records of earthquakes in chronological order with primarily the following event's information: arrival date and time (t_a), epicenters (latitude l_a , longitude l_o) with focal depth d_e, magnitude (a measure of size/intensity) m_a of event. However, the seismic catalog is also coined by some authors that generally includes the arrival time, amplitude, phase picks, and other metadata like moment tensor solutions, macroseismic information, tectonic summaries, focal mechanisms, maps, etc., provided by agencies running seismic networks or downloaded from a website. Recent scientific and technological advancement has enabled seismologists to produce standard/unified earthquake catalogs that provide a comprehensive list of events with detailed information on particular geographic regions. Here, well-known and frequently used catalog and provider agencies are described:

- **USGS Common Catalog** (USGS 2024) (COMCAT) provides several catalogs with real-time updation and integration results obtained from the USGS global and regional networks. However, in this, events are added and revised with the removal of duplicate events by coordinating with each other in near real-time. Generally, COMCAT provides complete information on worldwide activity with magnitudes greater than about 4.5. However, many countries (regions) produce catalogs of smaller earthquakes that occur within their regions of interest.
- **Global Centroid Moment Tensor** (Ekström et al. 2012) (CMT) Catalog developed by researchers at Harvard initially and then Columbia University is another source of information that comprises more than 50,000 post-1976 earthquake seismic moments

with information on the faulty geometry of the events. This catalog is very helpful for seismologists who want to study earthquakes and tectonics.

- **International Seismic Center (ISC), Global-Earthquake-Model (GEM)** (Storchak et al. 2015) ISC-GEM Catalog is the UK-based agency that aggregated many of the catalogs. This historic catalog contains many older events with relocation using novel algorithms, tools, and earth models. It provides a more consistent set of earthquake hypocenter and magnitude estimates for improving the quality of solutions at the time. This GEM catalog regularly evolves and updates the information based on the integration with regional networks, and thus, the magnitude threshold is lower compared to another global historical catalog.
- **Other Catalogs:** Several other regional catalogs are accessed according to their applicability, preferred region, and the contained information. Some of the catalogs are Italian earthquake catalog-CPTI15 (Rovida et al. 2020), European Preinstrumental Earthquake Catalog-EPICA (Rovida et al. 2022), Instrumental Earthquake Catalogue for Iceland and the northern Mid-Atlantic Ridge (ICEL-NMAR) (Jonasson et al. 2021), Southern California Earthquake Data Center (SCEDC) (Hauksson et al. 2020), National Seismic Hazard Mapping Project (NSHMP) Earthquake Catalog (Petersen et al. 2015), Northern California Earthquake Data Center (NCEDC) catalog (NCEDC 2021), Kandilli Observatory and Earthquake Research Institute (KOERI) (Cambaz et al. 2019), Japan Unified hI-resolution relocated Catalog for Earthquakes - JUICE (Yano et al. 2017), and International Institute of Earthquake Engineering and Seismology (IIEES), Iran (Mousavi-Bafrouei and Mahani 2020) and many more.

Earthquake catalog is also outlined as: (1) pre-1900, a long-term record of earthquakes based on pre-historic (paleoseismicity) and pre-instrumental and macroseismic information. They are prepared and collected through a trenching mechanism by paleoseismological investigations (Becker et al. 2005; Fumal et al. 1993; Schnellmann et al. 2002). (2) Historic, obtained from the assessment of an intensity field, seismic waveform analysis from early instruments, recorded on paper, rarely scanned and digitized. Mainly, they cover the period from the first human interventions to the onset of instrumental catalogs (Bakun 1999; Toppozada et al. 2002). (3) Instrumental, generated with the help of dense seismic network by automatic data transfer mechanism, processing and then delivering a location and magnitude information of earthquakes that occurred since the 1970 s or later (Lolli et al. 2020; Morozov et al. 2018). The pre-historical and historical seismicity catalogs are essential for evaluating long-term seismic hazards; instrumental catalogs are mostly used as resources for a variety of applications in statistical seismology.

2.2 General workflow for catalog generation

Over the years, seismologists have made a lot of efforts to detect the best possible estimates of the event locations, origin times, and magnitude information after the ground shaking due to earthquakes. The complete procedure for estimating these parameters requires rigorous research work along with a variety of seismic instruments for calibration and sensing mechanisms, related software for data pre-processing, coda, and algorithms. The traditional workflow for catalog construction to obtain reliable and best possible estimates of earthquake records in the form of a catalog is summarized as follows:

- **Seismic Data Collection and Management**: Initially, raw seismic waveform data are acquired from the recording stations (seismic networks e.g., USGS, IRIS, local seismic agencies) using seismometers, accelerometers, or geodetic instruments (GPS, InSAR) to detect ground motion due to earthquakes (Goulet et al. 2021; Haddadi et al. 2008; Clinton and Heaton 2002). In this, varieties of seismometers are utilized, e.g., short-period, long-period, strong-motion, strainmeter, tiltmeter, broadband, etc., with real-time and offline seismic monitoring software for detection and management.
- **Event Detection and Phase Picking:** Event detection is carried out to identify earthquake signals from continuous seismic waveform data either manually or automatically. Any false detections due to multiple sources, such as mine blasts, wind, human activity, ocean waves, etc., are filtered out to obtain a reliable and accurate earthquake record. The automatic detection algorithms e.g., short and long-term averages (STA/LTA) (Allen 1978; Sharma and Nanda 2020), neural networks (Gentili and Michelini 2006), higher-order statistics (Saragiotis et al. 2002), autoregressive methods (Sleeman and Van Eck 1999) and machine learning/deep learning models are frequently used for event detection. The arrival times of seismic phases (mostly P- and S- phase) are identified (picked) for locating an earthquake from 3D-component seismograms. Nowadays, with the improvement of computational power and memory capacity, deep learning and AI-based tools are extensively used instead of classical methods like AIC for automatic phase picking (Dokht et al. 2019; Chen et al. 2019; Saad et al. 2018; Perol et al. 2018; Mousavi and Beroza 2023). The commonly used software/packages for phase picker and association are: CDRP_TF (Zhou et al. 2019), EQTransformer (Mousavi et al. 2020), GPD (Ross et al. 2018), PhasePapy (Chen and Holland 2016), PhaseLink (Ross et al. 2019), PhaseNet (Zhu and Beroza 2019), S-SNAP (Tan et al. 2019), and EQTransformer.
- **Earthquake Location Determination:** In this procedure, earthquake locations are based on the non-linear inversion problem that aims to estimate the hypocentral parameters (origin time, epicentral locations: latitude, longitude, and depth). It considered travel-time and velocity models of the earth as known parameters and identified P- and S-wave phases on a given regional seismic network. 1D and 3D velocity models are considered to improve precision in hypocentral estimations. Preliminary, a classic 1D earthquake location algorithm called Hypo71 is used; later on, double-difference methods are more popular due to the high-precision relative location results (HypoDD (Waldhauser and Ellsworth 2000)). Probabilistic and grid-search methods are other non-linear (NonLinLoc) approaches used for locating the earthquake (Tunçel 2024; Gokalp 2024; Lomax et al. 2000; Stein and Wysession 2009). Other earthquake location software packages are: HYPOELLIPSE (Lahr 1989), HYPOINVERSE (Klein 2002), HYPOSAT (Schweitzer 2001), Neighborhood algorithm (Sambridge 1999a, b), NonLinLoc (Lomax and Curtis 2001) (for single event) and Bayesloc (Myers et al. 2007), COMPLOC (Lin and Shearer 2006), GrowClust (Lomax et al. 2009), mloc (Ritzwoller et al. 2003) (for multiple event). LOKI (Grigoli et al. 2014), QuakeMigrate (Winder et al. 2019), and easyQuake (Walter et al. 2021).
- **Magnitude Calibration:** Earthquake magnitude is estimated using a variety of magnitude scales such as Local Magnitude (ML), Moment Magnitude (Mw), Body-Wave (Mb), Surface-Wave Magnitude (Ms), etc. Local Magnitude is based on the logarithmic amplitude of the recorded seismic wave suitable for small local earthquakes (Richter

scale (Richter 1935)). Moment Magnitude (Mw) is derived from seismic moment rather than amplitude (Hanks and Kanamori 1979). Body wave (Mb) and surface wave magnitude (Ms) are based on the magnitude of body wave and surface wave, respectively. Recently, technological advancement through ML/DL algorithms improved the magnitude estimation procedures as reported in (Mousavi and Beroza 2020; Zhu et al. 2021; Meng et al. 2023; Ristea and Radoi 2021).

- **Quality and Location Uncertainty Analysis:** The accuracy and reliability of an earthquake catalog depend on waveform data quality and the level of uncertainty in the event location. Before compilation, validation, and distribution of the earthquake catalog, the construction mechanism is refined and validated with improved station coverage and azimuthal resolution, minimizing travel-time and phase picking errors, less variability in magnitude calibration, improved depth constraints, and incorporating additional phase information in the procedure. Nowadays, template matching (matched-filtering), relocation mechanism, relative magnitude calibration, and other AI-based advanced tools are utilized to acquire reliable earthquake records.
- **Compilation and Distribution:** This “waveform in catalog out" procedure that contains earthquake events (includes metadata such as event ID, date/time, coordinates, depth, magnitude, and uncertainty values) is compiled and stored in the structured database, e.g., CSV, SQL, QuakeML, GeoJSON with tools such as ObsPy, USGS ComCat API, GMT (Generic Mapping Tools), and QGIS for further processing, exportation and research.

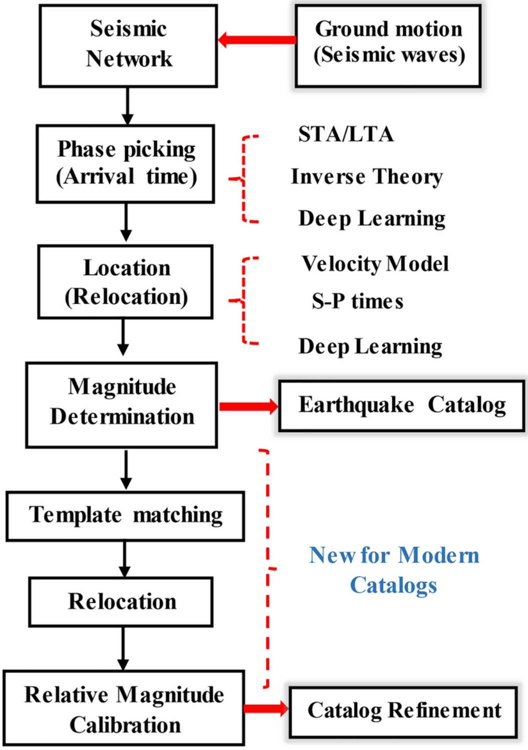
2.3 Challenges and applications

The catalog construction is a very challenging task and is not a unique procedure due to variability and uncertainty in the selection of human-selected computational tools, calibration instruments, sensors, software, and data processing mechanisms at different stages of the workflow. In recent years, seismologists minimized human inference or nearly eliminated it to make the laborious catalog construction workflow with a fully automated procedure (Jiao and Alavi 2020; Al Banna et al. 2020) instead of the traditional manual mechanism. Nowadays, AI-based intelligent systems with more deep learning components are applied at each stage, illustrated in Fig. 6. However, some challenges based on the hardware and software perspective are summarized as follows:

1. Hardware Infrastructure: In recent years, seismic networks have significantly improved in terms of hardware infrastructure by considering ultra-dense seismic instruments like nodal arrays, fiber-optic sensing technologies for regional and local earthquake monitoring (Shearer et al. 2023; Catchings et al. 2020; Li 2021; Nayak et al. 2023). They are capable of providing high-resolution quality data, better coverage density, and instrumental diversity. However, with these technological advancements, understanding of data characteristics of fiber-optic sensing mechanisms is challenging to impact observational seismology. Nowadays, distributed acoustic sensing is widely used for real-time earthquake monitoring and has the potential to become next-generation permanent networks (Paitz et al. 2021; Fernández-Ruiz et al. 2022; Zhan 2020).

2. Software Infrastructure: Due to the rapid progress in the development of machine learning (ML) approaches, data processing mechanisms, and handling large volumes of data related to distinct seismic regions (software infrastructure), it is reliable to store, transfer,

Fig. 6 Workflow for obtaining an earthquake catalog



visualize, and process big models and datasets (Mousavi and Beroza 2023, 2022; Jiao and Alavi 2020; MacCarthy et al. 2020). Nowadays, phase picking, association, location, and matched filter techniques are not only capable of finding large earthquakes but also locating small events with varying magnitudes beyond human perception limit with good precision and accuracy (Mousavi et al. 2020; Zhou et al. 2022). Real-time ML significantly improved the EEW systems by considering the fact that electronic signals travel much faster than seismic waves. It helps to generate pre-alerts based on the first P-wave arrivals that travel faster than S-wave and surface wave phases responsible for the strongest ground shaking. Rapid progress in ML also enhances the ground-motion prediction (Joshi et al. 2024; Khosravikia and Clayton 2021), tomography (Feng et al. 2022) and illuminating geophysical structures (Ren et al. 2020), earthquake geodesy (Crocetti et al. 2021; Dittmann et al. 2022) and non-inertial deformation (Gualandi et al. 2020; Lin et al. 2021). Still, ML is applied without considering the physical mechanism associated with a region of interest; in the future, a hybrid modeling framework needs to be developed to obtain synergy between domain scientists and data-driven ML methods (Zhu et al. 2023).

2.4 Catalog completeness

Earthquake catalogs do not provide a comprehensive record of earthquakes across all magnitude levels. Before applying any clustering algorithms, it is essential to evaluate the earthquake catalogs' quality, consistency, and completeness. This assessment involves determining a specific magnitude threshold known as the magnitude of completeness, denoted as

M_c. M_c is the lowest magnitude above which all earthquakes are considered to have been reliably recorded. It is also the magnitude above which the observed earthquake frequency adheres to the Gutenberg-Richter law (GR law), a fundamental seismic principle. The methods for evaluating M_c are broadly classified into two categories: (1) network-based methods (Schorlemmer and Woessner 2008; D'Alessandro et al. 2011) and (2) catalog-based methods ((Rydelek and Sacks 1989; Woessner and Wiemer 2005)). Network-based methods rely on a seismic network's detection and sensitivity characteristics, taking into account prior knowledge about station density and distribution. In contrast, catalog-based methods operate under a different definition of the magnitude of completeness. M_c is determined as the smallest magnitude at which the Frequency Magnitude Distribution (FMD) deviates from the Gutenberg-Richter (GR) law. When we compare these two definitions of the magnitude of completeness, it becomes apparent that Network-based methods generally offer advantages over catalog-based methods. However, establishing this fact is not straightforward, as it necessitates a deep understanding of seismic activity and the intricate process of combining waveforms from two separate seismic events, which is challenging.

Several methods for estimating the completeness magnitude (M_c) in seismic catalogs have been proposed. The Maximum Curvature method, introduced by Wiemer and Wyss in the year 2000 (Wiemer and Wyss 2000), is a non-parametric and fast approach. It involves determining the maximum of the first derivative of the FMD. Typically, it identifies the magnitude bin with the highest frequency in the non-cumulative FMD, aligning with the peak of the first derivative of the FMD. Another method, the M_c by b-value stability method by (Cao and Gao 2002), estimates M_c by analyzing the stability of the b-value concerning a cutoff magnitude (M). This approach aims to stabilize the b-value numerically, and Woessner and Wiemer 2005 introduced an uncertainty measure for the b-value. M_c is then determined as the first magnitude where the difference between the mean b-value and the evaluated b-values for successive cutoff magnitude bins is within a specified uncertainty. Finally, the Goodness-of-Fit Test (GFT), also proposed by Wiemer and Wyss in 2000 (Wiemer and Wyss 2000), estimates M_c by comparing synthetic data with the observed FMD. The test assesses goodness of fit using the R(a, b, M_c) parameter, with M_c defined as the first cutoff magnitude at which R reaches a predefined value of 95%.

Figure 7 illustrates the frequency magnitude distribution of the GR relationship (in log scale) for the earthquake sequences that occurred in the Himalayas during 2001-2024. Here, M_c is determined from the maximum likelihood solution with value = 4.5. The b-value= 1.11 ± 0.01 is computed for a 0.1 magnitude increment.

3 Fundamental empirical laws

This section briefly introduces well-established empirical relations/laws that are the basis for characterizing the clustering feature of seismicity (i.e., aftershock distribution) in a statistical sense based on spatial, temporal, and intensity information.

Gutenberg-Richter law: It describes the frequency-magnitude distribution (FMD) that shows the number of occurrences of earthquakes for the given magnitude *m* in a seismically active region during the finite time interval. It is an empirical relation defined as

$$N(m) = 10^{a-bm}, \tag{1}$$

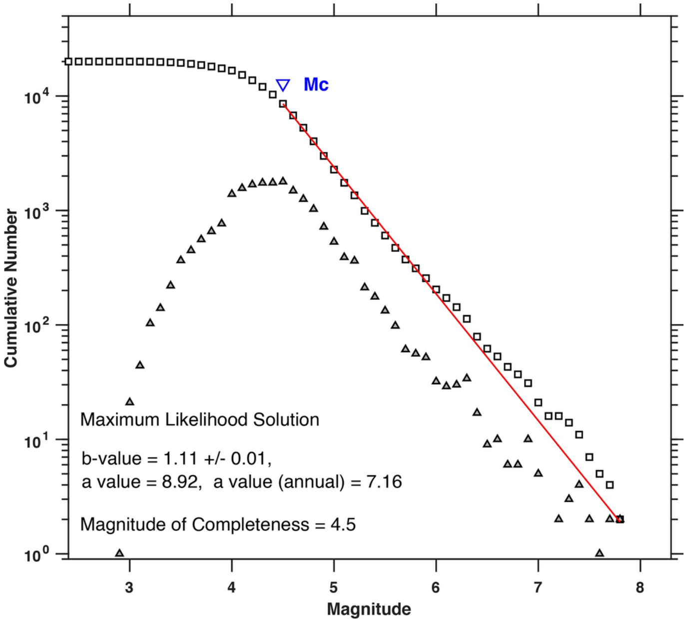


Fig. 7 Gutenberg-Richter relation and b-value with its standard deviation. It also calculates the Magnitude Completeness (M_c-value = 4.5) using the Maximum Curvature method for events that occurred in the Himalayas from 2001 to 2024

where *a* represents the seismicity level, and *b* is the slope parameter (called b-value) of the magnitude frequency curve, which is commonly close to 1.0 in seismically active regions.

The clustering characteristics with spatiotemporal deviation due to the occurrence of foreshock-aftershock sequences are addressed through this relation (FMD curve) where *b*-values are substantially smaller than the total one (Srivastava et al. 2015; Ali and Abdelrahman 2024). It is also revealed that an apparent decrease in the b-value (G-R law) for some duration has proven a promising precursor in high-magnitude earthquake forecasting (Smith 1981; Peng et al. 2021a; Zhang et al. 2019).

Omori-Ustu Formula: The aftershocks decay after the occurrence of mainshock is defined by an empirical relation referred to as the Omori-law (Omori 1894). It is expressed as:

$$v(t) \approx \frac{k}{c+t} \tag{2}$$

where *v* is the frequency of aftershocks (independent of magnitude), *c* is the time offset parameter that accounts for short-term incompleteness in aftershock detection, and *k* is a proportionality constant that determines the initial aftershock rate immediately following the mainshock. Later on, it was modified by Utsu in 1961 (Utsu 1961) with a third parameter *p*.

$$v(t) = \frac{k}{(c+t)^p} \tag{3}$$

It modifies the decaying rate, typically in the range of 0.7 to 1.5. It attracts considerable attention from the geophysical community due to its usefulness in estimating the probability of future aftershock occurrence.

Bath-law: Bath's law states that the difference ΔM in the magnitude of a mainshock and its largest aftershock is independent of mainshock magnitude (Båth 1965). The reference value is $\Delta M = 1.2$ in literature with some deviations as reported in Console et al. (2003) and Guglielmi et al. (2022). The meaningful interpretation of Bath's law is found in Lombardi (2002), Apostol (2020) and Helmstetter and Sornette (2003).

4 Clustering algorithms for seismicity analysis

Clustering algorithms provide a mechanism to group the related earthquakes based on their spatial, temporal, magnitude, and other information with significant correlations among them. Clustering is an essential approach in seismology that facilitates the study of earthquake-triggering mechanisms and stress transfer processes. Most of the algorithms identify and associate events based on spatial-temporal proximity, and some are based on several seismicity indicators, empirical laws, and stochastic models. This section provides a comprehensive discussion on a variety of clustering algorithms (models) proposed with consideration of different hypotheses, parameters, and assumptions in their methodologies by authors.

4.1 Based on K-means algorithm

K-means algorithm for clustering is a widely accepted approach and has popularity due to its simple implementation and computational efficiency (Hartigan and Wong 1979; Jain 2010). It is a centroid-based hard partitioning algorithm for making the non-overlapping clusters from the given unlabeled large datasets with a fast convergence rate. If $X = (x_1, ..., x_p)$ is set of data points, being $x_i = (x_{i1}, ..., x_{id})$ a vector with d features. Within such a set, and after providing the number of partitions, this algorithm returns the K stable centroids $(c_1, c_2, ..., c_k)$ and the formed clusters $(C_1, C_2, ..., C_k)$ when the algorithm converges to a local minimum of the squared distance (Euclidean norm) between the empirical mean of a cluster (centroid) and the data points in a cluster

$$\sum_{k=1}^{K} \sum_{i \in C_k} \|x_i - c_k\|^2 \tag{4}$$

(Hall et al. 2018) introduced a K-means-based clustering model in understanding fault activity and seismic hazards in the African-Arabian rift system. They considered the seismic moment to observe the spatial variations and look-ahead time concerning the next major release of seismic energy. The KL-index is used for cluster validation and for a correlation to the major structural segmentation of the rift. Similarly, (Weatherill and Burton 2009) addressed a weighted K-means cluster analysis for determining uniform seismic source zones to do the probabilistic seismic hazard analysis in the Aegean. They described a point-source K-means approach for capturing variation in the hypocentral distribution in a region. Then, a line source development algorithm is developed to trace the active faults with known fault ruptures in the Aegean. Krzanowski and Lai's (KL) index is used as a cluster quality indicator, and the robustness of the method is justified by considering different subsets of the observed earthquake catalog.

K-Means cluster analysis in earthquake epicenter clustering is reported in Novianti et al. (2017). This study explores earthquake epicenter clustering in Bengkulu Province, utilizing tectonic earthquake data from January 1970 to December 2015 obtained from the Meteorological, Climatological and Geophysical Agency (BMKG). K-means clustering with the Euclidean distance method is employed, considering variables such as latitude, longitude, and magnitude. The optimal number of clusters, determined using the Krzanowski and Lai (KL) index, is found to be 7. Rehman et al. (2014) also reported a K-means-based approach for identifying spatial differences in seismicity, and it forms a basis for delineating seismogenic sources in Pakistan and the surrounding regions. They have also used the KL index in addition to the seismic hazard contextual metric to find the optimal number of clusters from the magnitude homogeneous earthquake catalog of Pakistan, including some portions of the neighboring countries of Afghanistan, Tajikistan, and India. Morales-Esteban et al. (2010) proposed a forecasting scheme based on a *K*-means clustering algorithm for a magnitude greater or equal to 4.5. They considered event magnitude, *b*-value, and the occurrence time of an earthquake as features in the analysis with the Silhouette index (SI) for cluster validity in Spain and Portugal. Similarly, (Morales-Esteban et al. 2014) reported an adaptive Mahalanobis distance function with incremental *K*-means algorithm to discover elliptical shapes clusters for constructing the accurate seismically vulnerable zones in Croatia and the Iberian Peninsula. The authors used four validity indexes: Silhouette Width Criterion (SWC), Davies and Bouldin index (VDB), Calinski-Harabasz index (VCH), and Area index in this approach.

Mato and Toulkeridis (2017) introduced a 'GEO K-means algorithm' to determine accurate clustering of the earthquake events registered after the main shock in Ecuador and radian contribution in the affected areas. The algorithm considers the precursor contextual information based on the correlation pattern between ground radiation anomalies and high-magnitude earthquakes in the clustering process and the use of the Silhouette index. Ramdani et al. (2015) use the concept of K-means to improve the seismic visibility for the subduction zone in Chile. The method considers magnitude and depth along with spatiotemporal data for locating the high seismic energy for risk assessment and study of an underlying dynamic process, respectively. Silhouette index with evidence of subduction zone beneath Gibraltar Arc and Andean region, reflected by centroid distribution used in this analysis. Recently, Yuan (2021) described an improved K-means by employing the space-time-magnitude (STM) distance for selecting the initial cluster centers based on maximum-minimum STM distance (Yuan 2021). In the paper, ANN-based seismicity indicators and the sum of squares error (SSE), Davies-Bouldin index(DBI), Calinski-Harabasz (CH) index, and SI-based cluster validity indices are used to improve the optimal number of samples in each cluster with different levels of magnitude distribution. This method was applied to the global seismic catalog from 1900-2019, which was obtained from the USGS.

K-means clustering is widely applied in spatiotemporal seismicity analysis for tasks like identifying seismogenic sources, seismic zoning, and hazard assessment. Its strengths include simplicity, computational efficiency, and adaptability through extensions like Monte Carlo simulations, data-field theory, and feature extraction. However, it struggles with irregular cluster shapes, sensitivity to initial conditions, and high computational demands for complex datasets. Applications range from global earthquake predictions to regional seismic vulnerability studies, but scalability and performance heavily depend on dataset quality and careful parameter tuning. The strengths and limitations of the K-means algorithm are reported in Table 1.

4.2 Based on fuzzy clustering

Fuzzy clustering algorithms (Bezdek et al. 1984) are primarily suitable for overlapping datasets where each data point may belong to multiple clusters based on a membership grade. The membership function, denoted as u_{ij}, represents the degree to which a data point x_i belongs to cluster j, satisfying the condition:

$$\sum_{j=1}^{K} u_{ij} = 1, \quad 0 \leq u_{ij} \leq 1, \quad \forall i \in \{1, 2, \ldots, N\}, \forall j \in \{1, 2, \ldots, K\}. \tag{5}$$

Unlike the K-means algorithm, where cluster boundaries are crisp, fuzzy clustering defines soft boundaries, making it a soft-partitioning algorithm. Ansari et al.. applied the Gath and Giva fuzzy clustering algorithm to determine potential seismic zones in Iran (Gath and Geva 1989; Ansari et al. 2009). This algorithm extends the fuzzy K-means algorithm by incorporating fuzzy maximum likelihood estimation (FMLE). The objective function for FMLE is given as:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{K} u_{ij}^m d_{ij}^2, \tag{6}$$

where m is the fuzzification parameter, d_{ij} is the Mahalanobis distance, and u_{ij} represents the membership grade. The algorithm estimates fuzzy hyper-volume and partition density index without prior assumptions on the number of clusters. Wang et al. (2012) proposed a method based on the Gustafson and Kessel fuzzy clustering method (GK-FCM), which adapts the distance metric dynamically. The covariance-adaptive distance measure is expressed as:

$$d_{ij}^2 = (x_i - v_j)^T A_j (x_i - v_j), \tag{7}$$

where A_j is the positive definite matrix that determines cluster shape. This approach integrates Principal Component Analysis (PCA) and evaluates cluster validity using indices such as the Partition Index (PI), Separation Index (SI), and Xie-Beni Index (XBI):

$$\mathrm{XBI} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{K} u_{ij}^m \|x_i - v_j\|^2}{N \min_{j \neq k} \|v_j - v_k\|^2}. \tag{8}$$

This method is demonstrated on a synthetic catalog and the well-known Landers earthquake (1992) sequences in Southern California for fault structure redefinition. Similarly, Gvishiani

Table 1 Comparative analysis of clustering approaches used for spatiotemporal seismicity analysis, highlighting their type, methodology, catalog, applications, strengths, and limitations

Based on	Method Name	Geographic region/ Earthquake Catalog	Applications/Outcomes	Strengths	Limitations
K-means	K-means + Monte Carlo simulation (Rehman et al. 2014)	Pakistan (1930–2007)	Identifies potential groups of seismogenic sources	Simple and computationally efficient; suitable for well-defined clusters	Struggles with irregularly shaped clusters and requires a pre-defined number of clusters
	K-means + S-T-M distance + ANN (Yuan 2021)	Global earthquake catalog (1900–2019)	Models earthquake magnitude prediction after clustering	Integrates machine learning for improved predictive capability	High computational complexity; sensitive to input parameters
	K-means (Point-source + line-source) (Weatherill and Burton 2009, 2010)	Aegean (1900–1999)	Delineates shallow seismic source zones	Effective for seismic zoning	Limited applicability to complex tectonic regions
	K-means + Monte Carlo Simulation (Burton et al. 2008)	Aegean (1900–2005)	Analyzes probabilistic seismic hazards	Enhances hazard assessment accuracy	Requires substantial computational resources for simulations
	K-means + Data-field theory + Entropy (Shang et al. 2018)	Chinese Yongshaba mine (April 2014)	Denoises microseismic data and selects initial centroids	Handles noisy datasets effectively	Limited scalability for large datasets
	K-means + Feature extraction + b-value (Morales-Esteban et al. 2010)	Spain and Portugal (1978–2007)	Forecasts earthquakes with magnitude ≥ 4.5	Incorporates b-value analysis for improved seismic predictions	Performance is dataset-dependent and computationally intensive
	K-means (Euclidean distance) (Novianti et al. 2017)	Bengkulu Province (1970–2015)	Clusters earthquake epicenters and determines the optimal number of clusters (7)	Simple and effective for analyzing spatial patterns in seismicity	Sensitive to initial cluster centers and may require feature scaling

Table 1 (continued)

Based on	Method Name	Geographic region/ Earthquake Catalog	Applications/Outcomes	Strengths	Limitations
	K-means + Mahalanobis distance (Morales-Esteban et al. 2014)	Iberian Peninsula, Croatia	Discovers elliptical clusters for seismic vulnerability analysis	Adapts to more complex cluster shapes; efficient with incremental updates	Computationally intensive with large datasets
	K-means + Silhouette index (Mato and Toulkeridis 2017)	Ecuador	Clusters earthquake events after the main shock, correlating with ground radiation anomalies	Considers precursor information for more accurate clustering	Relies on the assumption that precursor patterns are valid across all events
	K-means + KL-index (Rehman et al. 2014)	Pakistan	Identifies spatial differences in seismicity and defines seismogenic sources	Utilizes a robust validation method for cluster accuracy	Requires careful calibration of the KL-index
Fuzzy Clustering	Gustafson-Kessel Fuzzy C-Means (GK-FCM) (Wang et al. 2012)	Southern California (Landers Earthquake, 1992)	Re-defines fault structure in the region based on clustering with adaptive distance norms	Detects clusters of different geometrical shapes; considers principalcomponent analysis	May not handle well-defined clusters as effectively as other methods
	Discrete Perfect Sets (DPS) algorithm (Gvishiani et al. 2013)	California	Determines earthquake-prone areas by clustering based on earthquake coordinates	Simple and effective for regional hazard analysis	Does not incorporate geophysical, geomorphological, or geological attributes
	Fuzzy Clustering + Monte Carlo Simulation (Ansari et al. 2015)	Unknown	Groups earthquake spatial locations and analyzes seismic hazards probabilistically	Integrates simulation for probabilistic analysis	Computationally intensive with complex hazard analysis

Table 1 (continued)

Based on	Method Name	Geographic region/ Earthquake Catalog	Applications/Outcomes	Strengths	Limitations
	Fuzzy Clustering in Seismology (Monem and Hashemy 2011; Shodiq et al. 2019; Mukhopadhyay et al. 2011)	Various regions	Applied in various seismicity analysis tasks	Adaptable to different seismicity problems	Requires careful selection of clustering parameters
Density/DBSCAN	SM-DBSCAN + hierarchical Agglomerative (Georgoulas et al. 2013)	Hellenic seismic arc (2000–2010)	Finds irregularly shaped spatiotemporal clusters	Suitable for non-spherical clusters; robust to noise	Parameter sensitivity (e.g., *epsilon*, min points) affects results
	Hierarchical DBSCAN + Vulnerability Indicators (Malakar and Rai 2022)	Himalayan (1970–2022)	Estimates the most active and vulnerable seismic regions	Combines clustering with vulnerability assessment	Lacks automation in parameter selection
	Point density function + FMD (Mukhopadhyay et al. 2010)	Burmese-Andaman and West Sunda Arc (1906–2008)	Provides 3D-relation on stress distribution between clustered seismic zones with focal depths	Visualizes complex stress distributions effectively	Limited to datasets with sufficient depth information
Self-Organized Map	SOM-based Clustering (Zamani et al. 2009, 2011; Mojarab et al. 2014; Ramezani Besheli et al. 2015)	Iran	Determines tectonic zoning and analyzes seismic activity patterns, especially in foreshock-mainshock-aftershock sequences	Effective for high seismic activity areas; offers dimensionality reduction and better visualization	May perform poorly in low seismic activity zones and with discontinuous seismic zones
Hierarchical	Agglomerative + Ward's method (Zamani and Hashemi 2004; Zamani et al. 2011)	Iran (1957 - 1979)	Reveals automated self-organized tectonic zoning	Captures nested clustering structures	Computational cost increases with dataset size

Table 1 (continued)

Based on	Method Name	Geographic region/ Earthquake Catalog	Applications/Outcomes	Strengths	Limitations
	Hierarchical + agglomeration distance coefficient (Hashemi and Mehdizadeh 2015)	Zagros (Iran)	Performs tectonic regionalization and improves understanding of regional tectonics	Effective for hierarchical data	Sensitive to choice of linkage criteria

et al. (2013) introduced a fuzzy-based Discrete Perfect Sets (DPS) algorithm for determining earthquake-prone areas in California. It leverages earthquake coordinates without considering geophysical, geomorphological, or geological attributes and is compared with the recognition method of Gorshkov et al. (2005). Ansari et al. (2015) reported a fuzzy clustering approach combined with Monte Carlo simulations to group earthquake spatial locations. This aids in identifying potential seismic sources and analyzing probabilistic seismic hazards. Several studies have applied fuzzy clustering to seismology (Monem and Hashemy 2011; Shodiq et al. 2019; Mukhopadhyay et al. 2011), demonstrating its versatility in seismicity analysis, fault structure redefinition, and probabilistic hazard assessment. However, while fuzzy clustering efficiently handles diverse cluster shapes, it requires careful parameter tuning and can be computationally intensive, as summarized in Table 1.

4.3 Based on density algorithms

Density-based clustering (DBC) algorithms have the ability to detect clusters of arbitrary shape and handle outliers present in a given dataset (Ester et al. 1996). These algorithms rely on the density of data points in the neighborhood defined by a radius ϵ and a minimum number of points *MinPts*. A core point in a dataset satisfies the condition:

$$|N_\epsilon(p)| \geq MinPts, \tag{9}$$

where $N_\epsilon(p)$ represents the set of points within the ϵ neighborhood of point p. If a point does not satisfy this condition but belongs to the ϵ-neighborhood of a core point, it is considered a border point; otherwise, it is classified as noise. Georgoulas et al. (2013) proposed a seismic-mass density-based clustering (SM-DBSCAN) scheme to determine potential seismic sources in the Hellenic arc. The algorithm considers earthquake magnitude (seismic mass) as a weight to each event and determines the accumulated neighborhood mass for each event for density estimation. The density function is defined as:

$$D(p) = \sum_{q \in N_\epsilon(p)} M_q, \tag{10}$$

where M_q is the magnitude of event q within the ϵ-neighborhood of p. The algorithm effectively detects non-spherical, noisy spatio-temporal clusters but is sensitive to parameters ϵ and *MinPts*. Scitovski developed 'Rough DBSCAN' (Scitovski 2018) to determine nonconvex shapes of seismic zones in Croatia. This method incorporates an adaptive mechanism for selecting ϵ dynamically, addressing the issue of parameter sensitivity. Liu et al. (2014) proposed a spatiotemporal shared nearest neighbors (SNN) clustering algorithm, where the similarity between points p and q is determined based on shared neighbors:

$$SNN(p,q) = |N_k(p) \cap N_k(q)|, \tag{11}$$

where $N_k(p)$ denotes the set of k nearest neighbors of point p. This approach is less sensitive to density variations and efficiently identifies foreshock and aftershock clusters. Wang et al. (2017) introduced a 'seismic density index' to quantify clustering intensity and seismic energy release in a region. A grid of interval Δ in longitude and latitude is defined, where each node is associated with an outer circle of radius R and an inner circle of minimum radius R_{min}. If r_{ij} is the distance between the j^{th} grid node and the i^{th} earthquake epicenter, the seismic density index $I_{j,t}$ for a node j at time t is given by:

$$I_{j,\ t} = \sum_{i=1}^{n} \frac{M_i}{\Delta m \ln(r_{ij})}, \quad R_{min} \leq r_{ij} \leq R. \tag{12}$$

Here, n represents the number of events, Δm is the difference between the threshold magnitude and the maximum magnitude, and M_i is the i^{th} event magnitude. Nanda and Panda (2015) introduced a fast density-based clustering by modifying the merging criterion in traditional DBSCAN, allowing for a more efficient clustering process. This algorithm was applied to determine hazardous zones in Japan by incorporating both magnitude and depth information from seismic catalogs. Potential source zones for Himalayan earthquakes were identified by Mukhopadhyay et al. (2011), utilizing 'point density' spatial statistics to determine clusters. A moving time-distance window technique was applied to reveal temporal clusters, delineating foreshock-mainshock-aftershock (FMA) sequences within previously identified spatial clusters. Overall, density-based clustering methods provide effective tools for seismic hazard assessment by identifying spatial and spatio-temporal earthquake clusters. However, their sensitivity to parameter selection remains a challenge that requires adaptive solutions.

4.4 Based on self organized map (SOM)

The Self-Organizing Map (SOM) is a type of artificial neural network that projects high-dimensional input data onto a lower-dimensional (typically two-dimensional) space while preserving topological properties (Kohonen 1982; Vesanto and Alhoniemi 2000). The SOM consists of a grid of neurons that are trained using competitive learning, where each input vector $\mathrm{x} \in \mathbb{R}^d$ is mapped to a best-matching unit (BMU) w_c in the grid using a distance metric, typically Euclidean distance:

$$c = \arg\min_i \|\mathrm{x} - \mathrm{w}_i\|, \tag{13}$$

where w_i represents the weight vector of the i^{th} neuron. During training, the weight vectors are updated using the learning rule:

$$\mathrm{w}_i(t+1) = \mathrm{w}_i(t) + \eta(t) h_{ci}(t)(\mathrm{x} - \mathrm{w}_i(t)), \tag{14}$$

where $\eta(t)$ is the learning rate and $h_{ci}(t)$ is the neighborhood function, often modeled as a Gaussian:

$$h_{ci}(t) = \exp\left(-\frac{\|\mathrm{r}_c - \mathrm{r}_i\|^2}{2\sigma^2(t)}\right), \tag{15}$$

where r_c and r_i are the positions of the BMU and neuron i on the grid, and $\sigma(t)$ is the neighborhood radius that decreases over time. SOM-based clustering has been applied by Zamani et al. (2009) to determine tectonic zoning in Iran and compared with hierarchical clustering (Ward's method). Similarly, Zamani et al. (2011) used SOM clustering along with Wilk's Lambda criterion to select the optimal number of clusters. In Mojarab et al. (2014), the effect of SOM input parameters on seismicity clustering in Iran was analyzed, demonstrating how different initialization techniques and learning parameters affect clustering results. A combination of K-means clustering and SOM was utilized by Ramezani Besheli et al. (2015) to analyze Iranian foreshock databases, revealing a strong correlation between foreshock clusters and large earthquake occurrences. The approach clusters seismic events into *K* groups by minimizing the intra-cluster variance:

$$J = \sum_{i=1}^{K} \sum_{\mathrm{x}_j \in C_i} \|\mathrm{x}_j - \mu_i\|^2, \tag{16}$$

where C_i is the i^{th} cluster with centroid μ_i. However, it is observed that SOM-based clustering is more effective in regions with high seismic activity, whereas in areas with low seismic activity, the results may be less interpretable, leading to discontinuous and fragmented cluster zones. Table 1 summarizes the strengths and limitations of SOM-based clustering techniques in seismicity analysis.

4.5 Based on hierarchical clustering

Hierarchical clustering is a widely accepted approach for seismicity partitioning, particularly in tectonically active regions. It represents clusters hierarchically in the form of a dendrogram, which provides a visual representation of nested clustering structures. This method begins by treating each data point as an individual cluster and iteratively merging the closest clusters until a predefined stopping criterion is met. Mathematically, hierarchical clustering can be represented as follows:

1. Distance Calculation: The dissimilarity between two data points x_i and x_j is measured using a distance metric, commonly the Euclidean distance:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \tag{17}$$

where x_{ik} and x_{jk} are the k^th features of data points x_i and x_j.

2. Linkage Criteria: Clusters are merged based on a chosen linkage function, such as:

– Single Linkage: The minimum distance between points in two clusters C_i and C_j:

$$d(C_i, C_j) = \min_{x \in C_i, y \in C_j} d(x, y) \tag{18}$$

– Complete Linkage: The maximum distance between points in two clusters:

$$d(C_i, C_j) = \max_{x \in C_i, y \in C_j} d(x, y) \tag{19}$$

– Average Linkage: The mean pairwise distance between all points in the two clusters:

$$d(C_i, C_j) = \frac{1}{|C_i||C_j|} \sum_{x \in C_i} \sum_{y \in C_j} d(x, y) \tag{20}$$

– Ward's Method: Merges clusters based on minimizing the increase in intra-cluster variance:

$$d(C_i, C_j) = \frac{|C_i||C_j|}{|C_i| + |C_j|} \|\mu_i - \mu_j\|^2 \tag{21}$$

where μ_i and μ_j are the centroids of clusters C_i and C_j. One key advantage of hierarchical clustering is that it does not require the number of clusters to be predetermined. For instance, Hashemi and Karimi (2016) employed hierarchical clustering to automatically identify homogeneous seismic sources and produce accurate earthquake magnitude prediction models. Their study tested the approach using non-spatial attributes, spatial location data, and combined datasets. The prediction models were then evaluated using decision trees, SVM, and kNN algorithms, with results showing improved accuracy after clustering. Additionally, hierarchical clustering has been applied in mining-induced seismicity analysis using Ward's minimum variance method, as demonstrated by Lurka (2021). Other notable applications include tectonic regionalization in Iran, where agglomerative hierarchical clustering combined with Ward's method was used to reveal self-organized tectonic zoning (Zamani and Hashemi 2004; Zamani et al. 2011). In another study, hierarchical clustering with an agglomeration distance coefficient was applied in the Zagros region of Iran to improve understanding of regional tectonics (Hashemi and Mehdizadeh 2015). The strengths of hierarchical clustering include its ability to handle hierarchical data and effectively capture nested structures, as reflected in Table 1. However, its limitations include sensitivity to the choice of linkage criteria and increased computational costs for larger datasets. The computational complexity for agglomerative hierarchical clustering is typically $O(n^2 \log n)$, making it less efficient for large-scale seismicity datasets.

4.6 Based on the graph (Network) theory

Earthquake data analysis using graph and network-based topologies has been extensively studied by Abe and Suzuki (2006). They analyzed earthquake data from California and

Japan, mapping seismic events onto evolving random networks. Their findings indicate that earthquake networks exhibit scale-free properties with degree distributions following a power law:

$$P(k) \sim k^{-\gamma}, \tag{22}$$

where $P(k)$ represents the probability of a node having degree k, and γ is a critical exponent typically observed in complex networks. Furthermore, these networks demonstrate small-world properties characterized by a high clustering coefficient C and a small average shortest path length L. The clustering coefficient is defined as:

$$C = \frac{1}{N}\sum_{i=1}^{N}\frac{2E_i}{k_i(k_i-1)}, \tag{23}$$

where E_i is the number of edges among the neighbors of node i, k_i is the degree of node i, and N is the total number of nodes in the network. (Abe and Suzuki 2007) investigated the temporal evolution of earthquake networks, observing that the clustering coefficient remains nearly constant before a major shock, experiences a sharp increase during the main shock, and then follows a power-law relaxation:

$$C(t) \sim t^{-\beta}, \tag{24}$$

where β characterizes the decay rate of the clustering coefficient over time post-event. Telesca et al.. (Telesca and Lovallo 2012; Telesca et al. 2015b) introduced the visibility graph approach for earthquake clustering analysis, utilizing earthquake occurrence times t_i and magnitudes M_i. In this approach, two events (t_i, M_i) and (t_j, M_j) are connected if:

$$M_j > M_i + \alpha \log(|t_j - t_i|), \tag{25}$$

where α is a tuning parameter that controls the visibility criterion. The advantages and limitations of graph-based earthquake analysis methods are summarized in Table 2.

4.7 Based on evolutionary computing

Evolutionary computation techniques are preferred due to their robustness, flexibility, diversity, and simple representation, making them suitable for capturing global solutions of complex, real-world optimization problems (Dumitrescu et al. 2000). Given increasing computing power, speed, and storage, evolutionary algorithms (EAs) are now routinely applied across diverse domains (Zhan et al. 2022). Some researchers have leveraged evolutionary computation for cluster analysis in seismicity. Sarafis et al. (2007) introduced a rule-based evolutionary algorithm for identifying non-overlapping clusters in high-dimensional datasets. This approach termed the Non-Overlapping Clustering with an Evolutionary Algorithm (NOCEA), employs a fitness function based on data coverage maximization:

Table 2 Comparative analysis of clustering approaches used for spatiotemporal seismicity analysis, highlighting their type, methodology, catalog, applications, strengths, and limitations

Based on	Method Name	Geographic region/ Earthquake Catalog	Applications Outcomes	Strengths	Limitations
Graph Theory	Earthquake network analysis (Abe and Suzuki 2006, 2007)	California, Japan	Analyzes earthquake data through growing random networks to detect complex network properties	Networks are scale-free with small-world properties; useful for detecting precursors to main shocks	High computational cost for large datasets
	Visibility graph approach (Telesca and Lovallo 2012; Telesca et al. 2015b)	Global	Analyzes inherent clustering of earthquakes based on occurrence time and magnitude	Captures dynamic clustering patterns effectively	Sensitive to input parameters like time and magnitude ranges
Evolutionary	TriGen (3D Genetic algorithm) (Martínez-Álvarez et al. 2015)	Iberian Peninsula (1978–2013)	Performs seismogenic zoning and correlates with geology	Explores large solution spaces effectively	Requires significant computational resources
	Fuzzy PSO (Nejad et al. 2021)	Iran (1900–2011)	Determines seismic source zones and associates with faults	Combines fuzzy logic with optimization for robust clustering	Sensitive to parameter tuning and prone to premature convergence
	Weighted K-means + PSO (Sheikhhosseini et al. 2021)	Zagros (4th century B.C. - 2019)	Delineates potential seismic sources	Enhances clustering accuracy using weights and optimization	Increased complexity due to hybrid approach
Point Process Model	Markovian Arrival Process (MAP) + DBSCAN (Bountzis et al. 2022)	Greece (2012–2019)	Shows regional variability in aftershock productivity and background rates	Incorporates temporal dynamics in clustering	Computationally intensive for large datasets
Neural Network	Feature Extraction + SOM (Zamani et al. 2009; Mojarab et al. 2014)	Iran (1965–2013)	Constructs tectonic maps and zoning	Learns complex patterns in seismic data	Requires substantial training data; prone to overfitting
	Feature extraction + SOM (Reyes and Cárdenas 2010)	Chile (1957–2007)	Performs seismic regionalization	Adapts to high-dimensional data effectively	Limited interpretability of clustering results
Deep learning	Deep NN + Parallel processing (Konstantaras 2020)	Greek vicinity (1966–1992)	Locates potential distinct seismic zones in the Ionian Sea	Handles large and complex datasets; scalable	Requires high computational resources and extensive training data
Evolutionary Computing	Non-overlapping Clustering with Evolutionary Algorithm (NOCEA) (Sarafis et al. 2007)	African-Eurasian-Arabian collision boundary	Finds non-overlapping clusters in high-dimensional seismic datasets	Uses genetic operators for effective clustering; robust for complex data	Requires significant computational resources and tuning of parameters

$$F = \sum_{i=1}^{N} w_i \cdot f(C_i), \tag{26}$$

where F is the overall fitness, C_i represents individual clusters, $f(C_i)$ quantifies cluster quality, and w_i is a weight factor controlling the contribution of each cluster. NOCEA utilizes axis-aligned hyper-rectangular clustering rules and novel semi-stochastic genetic operators with an integer-valued encoding scheme. For a given dataset $D = \{x_1, x_2, \ldots, x_N\}$ in $\mathbb{R}^d$, the clustering objective aims to partition D into k clusters $\{C_1, C_2, \ldots, C_k\}$, where each cluster C_i satisfies:

$$\bigcup_{i=1}^{k} C_i = D, \quad C_i \cap C_j = \emptyset, \quad \forall i \neq j. \tag{27}$$

However, NOCEA is sensitive to parameter tuning and prone to premature convergence, making it necessary to fine-tune parameters such as mutation rate μ and crossover probability p_c. The evolutionary update step follows:

$$C^{(t+1)} = C^{(t)} + \alpha \cdot \nabla F(C), \tag{28}$$

where α is a learning rate controlling convergence speed. Both traditional and evolutionary-based clustering techniques exhibit distinct advantages and limitations in seismicity analysis, depending on dataset characteristics and methodology, as summarized in Table 2.

4.8 Based on swarm intelligence

Sheikhhosseini et al. (2021) introduced a combined approach utilizing weighted K-means clustering analysis and Particle Swarm Optimization (PSO) to automatically identify the global optimum clusters in a region. The clustering process aims to minimize the within-cluster sum of squares (WCSS), given by:

$$WCSS = \sum_{i=1}^{k} \sum_{x_j \in C_i} \|x_j - \mu_i\|^2 \tag{29}$$

where k is the number of clusters, C_i represents the set of points in the i-th cluster, x_j is a data point, and μ_i is the centroid of cluster C_i. To determine the optimal number of clusters, this study employs Davies-Bouldin's measure DB and Chou-Su-Lai's measure CS. The Davies-Bouldin index is defined as:

$$DB = \frac{1}{k} \sum_{i=1}^{k} \max_{i \neq j} \left(\frac{s_i + s_j}{d_{ij}} \right) \tag{30}$$

where s_i and s_j denote the average intra-cluster distances for clusters i and j, and d_{ij} is the Euclidean distance between cluster centroids μ_i and μ_j. Nejad et al. (2021) introduced an optimized version of the fuzzy clustering algorithm based on PSO, where two objective functions are minimized:

$$f_1 = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d(x_j, v_i) \tag{31}$$

$$f_2 = \sum_{j=1}^{n} \min_i d(x_j, F_i) \tag{32}$$

where c is the number of clusters, n is the total number of events, u_{ij} represents the membership degree of event x_j to cluster i, m is the fuzzification parameter, $d(x_j, v_i)$ is the distance of event x_j from cluster center v_i, and F_i denotes the nearest fault line to event x_j . This method is applied to identify the main fault structures in the Fars and Kerman provinces of southwestern and southeastern Iran, respectively, using PSO to optimize the cluster formations by iteratively updating particle positions according to:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i^{best} - x_i^t) + c_2 r_2 (g^{best} - x_i^t) \tag{33}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{34}$$

where v_i^t and x_i^t are the velocity and position of the i-th particle at iteration t, ω is the inertia weight, c_1, c_2 are acceleration coefficients, r_1, r_2 are random numbers in $[0, 1]$, p_i^{best} is the personal best position, and g^{best} is the global best position. The integration of these clustering techniques with PSO enhances the accuracy of seismic source identification and fault association, contributing to improved earthquake hazard assessment.

4.9 Based on point-process modeling

The occurrence of earthquakes in the spatio-temporal domain is considered to be a self-exciting process and described with space-time models (point-process) in the form of conditional intensity function. Initially, several authors have reported different forms of space-time models to explore clustering characteristics of any region, especially the most popular Epidemic Type Aftershock Sequence (ETAS) model that offers a realistic and quantifiable approximation (Ogata 1998, 1999, 2017) of earthquake sequences in time, space, and magnitude domain. Mathematically, if assume probability $P_{\Delta t, \Delta x, \Delta y}(t, x, y|H_t)$ of an earthquake, occurs in small time interval between t and $t + \Delta t$, and small geographic region $[(x, x + \Delta x)] \times [(y, y + \Delta y)]$, where $H_t = (t_i, x_i, y_i, M_i); t_i < t$ is the history of events with occurrence times t_i up to t, corresponding epicenters (x_i, y_i) and magnitude M_i, then conditional intensity function is $\lambda(t, x, y, |H_t)$ defined as

$$\lambda(t, x, y, |H_t) = \lim_{\Delta t, \Delta x, \Delta y \to 0} \frac{P_{\Delta t, \Delta x, \Delta y}(t, x, y|H_t)}{\Delta t \Delta x \Delta y} \tag{35}$$

With the assumption of stationarity, it is also extended in the following form

$$\lambda(t, x, y, |H_t) = \mu(x, y) + \sum_{\{i; t_i < t\}} g(t - t_i, x - x_i, y - y_i; M_i) \tag{36}$$

where the background seismicity rate $\mu(x, y)$ is a function of space, but not as time. It can model the seismicity rate before and after strong earthquakes (mainshock) and quantify the increased earthquake hazard after a mainshock by incorporating the triggering ability of foreshocks, a mainshock, and subsequent aftershocks.

4.10 Other diversified clustering approaches for seismicity analysis

1. Schuster spectrum-based approach (Ader and Avouac 2013): The unknown periodicities present in an earthquake catalog are determined by computing a spectrum of Schuster p-values. This spectrum also provides information about the deviation from a sinusoidal function of the periodicity of the seismicity rate. It helps to find the declustering accuracy of the given earthquake catalog. This method is applied to the Himalayan region with annual variations of the seismicity rate of amplitude up to 40%, while no other periodicity appears.

2. Morisita index-based approach (Golay et al. 2014; Telesca et al. 2015a): Morisita index-based clustering analysis of seismicity is carried out by analyzing spatial patterns present in the earthquake catalogs. In this, a given earthquake catalog is covered by a regular grid of changing size, and then Morisita index I_δ measures how many times it is more likely to randomly select two sample events from the same quadrant. It is defined by

$$I_\delta = \frac{Q}{N(N-1)} \sum_{i=1}^{Q} n_i(n_i - 1) \tag{37}$$

where the diagonal length of the grid is taken as quadrant size δ, Q is the number of quadrats necessary to cover the spatial region, n_i is the number of events in the i^{th} quadrant, and N is the total number of events. The fluctuations in I_δ with δ around one are used to categorize the characteristics of events in the spatial domain. The multi-point Morisita index (m-Morisita) version considers m points with $m \geq 2$.

3.Multi-resolution wavelet approach (Telesca et al. 2004): In this method, a standard deviation of the wavelet coefficient $\sigma_{wav}(m)$ is determined by considering an earthquake series of time intervals between successive events τ_i, $i = 1, ...L$, where L is the length of the given series. It is defined as

$$\sigma_{wav}(m) = \left[\frac{1}{N-1} \sum_{n=1}^{N} (W_{m,n}^{wav} - \langle W_{m,n}^{wav} \rangle)^2) \right] \tag{38}$$

Here, the discrete-time sequence of the time series is transformed in terms of the wavelet coefficients using DWT as follows:

$$W_{m,n}^{wav} = 2^{(-m/2)} \sum_{i=1}^{L} \tau_i \psi(2^{-m} * i - n) \tag{39}$$

where the scale variable *m* and translation variable *n* are integers, L represents the total number of intervals to be analyzed and ψ is the wavelet function. *N* is the number of wavelet coefficients at the given scale *m*. The temporal evolution of seismicity is analyzed by varying the $\sigma_{wav}(m)$ at different time scales. This method analyzes two earthquake sequences that occurred in Italy, Umbria-Marche, and Irpinia, in 1986-2001.

4. Clustering in Ergodic framework (Thirumalai and Mountain 1993): The complex network of earthquakes is also explained in an Ergodic framework with the help of the Thirumalai-Mountain (TM) metric. It provides information about the effective ergodic periods (state of metastable equilibrium) that can be disrupted by large earthquake events. For a system comprised of *N* particles and an observable *G*, it is defined as

$$\Omega_G(t) = \frac{1}{N} \sum_{j=1}^{N} [g_j(t) - \langle g \rangle]^2 \tag{40}$$

where

$$g_j(t) = \frac{1}{t} \int_0^t G_j(t')dt' \tag{41}$$

is the time average of a individual particle, $G_i(t)$, and

$$\langle g \rangle = \frac{1}{N} \sum_{j=1}^{N} g_j(t) \tag{42}$$

is the ensemble average of that temporal average over the entire system. Tiampo et al. (2003) applied TM metric to California earthquake catalog with magnitude $m \geq 3$ to ensure completeness of the catalog. Here, the region is discretized by dividing it into a set of grid cells and considering the cumulative number of events $n_i(t)$ in each i^{th} box until time step *t*. It represents the released seismic energy at i^{th} location, and then strong evidence of ergodicity is determined in a region through numerical simulation.

5. Entropy-based approach (Nicholson et al. 2000): Earthquake hypocenter distributions are quantified by analyzing the entropy of a 3-D event set (longitude, latitude, and focal depth). It is determined with the help of Voronoi cells by estimating the event density from its volume. This concept is utilized to classify the different tectonic regimes: mid-ocean ridges, subduction zones, and intra-plate seismicity for the global earthquake catalog (EHB) and SIL network. The configurational entropy *H*(.) is also defined in (Goltz and Böse 2002) to detect the phase transition during the earthquakes with the definition of a critical point. It is applied to the Landers earthquake sequence (1992, M7.3) that occurred in Southern California. The increment in *H*(.) before the occurrence of mainshock reveals the presence of clustering and is useful to identify the aftershocks present in a catalog.

Tables 1 and 2 provides an extensive overview of methodologies based on the different fundamental concepts of clustering mechanisms. Both tables showcased the variety of approaches with their selected region/catalog, applications, strengths, and limitations of each. By comparing the different approaches as mentioned in Tables 1 and 2, researchers can gain valuable insights into the effectiveness and limitations of each method. Additionally, this table serves as a useful resource for practitioners in the field of seismology, who can use this information to select the most suitable method for their specific applications.

4.11 Clustering algorithms for earthquake swarms

Earthquake swarms are also considered a group of events (clusters) in the spatiotemporal domain, but their occurrence and characteristics differ significantly from the aftershock cluster sequences that appear due to the triggering mechanism. Their spatiotemporal occurrence is yet not fully observed but is often interpreted in response to the aseismic transients/deformation, change in fluid pressure (fluid migration), or magmatic activity in the volcanic and hydrothermal regions. In the time domain, aftershock-mainshock clusters are characterized by a power law as per modified Omori relation, whereas neither Omori-law nor any other empirical law applicable to describe the temporal evolution of swarm activity is considered to be much smoother Hainzl (2003). They are defined by an increase in seismicity rate without any explicit triggering of the mainshock. Peng et al. (2021b) proposed a swarm detection method based on three distinct methods: ETAS, NN13, and Re85 for Taiwan. They are found at locations with high seismicity rates and occur in areas experiencing high creep rates and episodic aseismic slip. Ito (1990) revealed the precise hypocenters of microearthquakes occurring in a swarm pattern with a spatial resolution of the order of 10 m for the Ashio region, Japan. Essing and Poli (2024) proposed a method to identify clusters comprised of earthquake swarms by exploiting space and time information of the seismicity related to the 2014 Alto Tiberina swarm sequence (Italy). Minetto et al. (2022) analyzed the spatiotemporal evolution of the Maurienne swarm (French Alps) earthquake cluster with the creation of a high-resolution catalog based on template matching, double-difference relocation, and moment magnitudes.

Zhang and Shearer (2016) reported a novel search method to identify earthquake swarms by finding the closest neighboring earthquakes in space and time and their comparison with the number of neighbors to the background events in larger space/time windows for seismicity near the San Jacinto Fault, California. Schneider et al. (2023) introduced a window-based search mechanism to discriminate the mainshock-aftershock or swarm-based clustering sequences for the Pacific Northwest. Sirorattanakul et al. (2024) proposed a deep-learning-based workflow to identify and locate swarm events between 2015 and 2022 at Groningen and also reported that propagating swarms do not always signify fluid migration. Im and Avouac (2023) derived a generalized approach for clustering due to the cascading of foreshocks, aftershocks, and swarms based on the Discrete Fault Network model governed by rate-and-state friction. Liu et al. (2023a) reported an initiation and revolution process and their complexities, especially for the 2013 Yunlong earthquake swarm based on the 3D fault geometry. Talebi et al. (2024) proposed a robust method to detect both swarm-like sequences and burst-like clustering patterns (aftershocks) based on nearest-neighbor distances (Tree graphs) and network analysis for north-central Iran.

5 Clustering evaluation metrics and methods for spatiotemporal seismicity analysis

Assessment of the obtained 'cluster quality' is an important consideration in capturing the spatiotemporal patterns, trends, and correlations in a seismically active region. The performance of earthquake clustering algorithms, especially in space and time and other well-connected features, is examined through various statistical tests, evaluation metrics (parameters), and other graphical judgments. Table 3 presents various performance metrics used in spatiotemporal earthquake clustering algorithms, categorized by clustering method. Each clustering technique has its own set of evaluation metrics, which are essential for understanding the quality, accuracy, and relevance of the clustering outcomes. These metrics not only help to validate the results of the clustering but also highlight the strengths and limitations of the methods used.

For K-means clustering, commonly applied in earthquake-related studies, metrics like the Xie & Beni index, Silhouette Index, and Krzanowski-Lai (K-L) index are used to assess the compactness and separation of clusters, providing insights into how well seismic events are grouped in distinct zones. These indices are crucial because they quantify the degree of cluster cohesion and separation. However, one limitation of these metrics is that they assume a predefined number of clusters, which can be a challenge in dynamic or poorly understood seismic zones where the number of clusters might not be clear in advance (Weatherill and Burton 2009; Rehman et al. 2014). In earthquake magnitude prediction studies by Kamat and Kamath (2017) and Yuan (2021), the Davies-Bouldin index, Sum of squares error, and Silhouette coefficient are applied. These metrics are important for assessing the accuracy of predictions, with the Davies-Bouldin index measuring the average similarity ratio between clusters, while the Silhouette coefficient assesses how similar an event is to its own cluster compared to other clusters. The limitation of these metrics is that they might not effectively account for highly variable or non-linear relationships in complex seismic data, leading to skewed results when such patterns are present.

Fuzzy clustering techniques, used in studies such as those by Ansari et al. (2009) and Gvishiani et al. (2013), apply Cluster quality index and density criteria. These metrics are important because they allow for the identification of overlapping clusters and account for uncertainty in earthquake event classifications. Fuzzy clustering is particularly useful when events are not clearly associated with one cluster, as is often the case in seismically active regions. However, the Cluster quality index and density criteria may not always capture the true nature of spatial and temporal relationships in densely packed clusters or in the presence of noise, potentially leading to inaccurate assessments (Mirrashid 2014). In magnitude prediction studies by Mirrashid (2014), R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) are applied, providing a robust measure of model performance. These metrics are particularly useful for validating regression models, but they may overlook the spatial and temporal aspects of clustering in seismicity, as they primarily focus on point-to-point accuracy.

In density clustering, applied in studies like those by Scitovski (2018) and Georgoulas et al. (2013), metrics such as fitness values and accuracy are used to assess the clustering's ability to capture dense regions of seismic events. These methods are particularly valuable in identifying earthquake hotspots or high-risk zones. However, fitness values and accuracy can be limited in regions where seismic activity is sparse or the data is highly fragmented,

Table 3 Listing of all performance metrics used for spatiotemporal earthquake clustering algorithms

Category	Purpose	Evaluation metric
	Delineation of Shallow Seismic Source Zones (Weatherill and Burton 2009) and Seismicity Partitioning (Rehman et al. 2014)	Xie & Beni, Silhouette Index, Calinski & Harabasz index, and Krzanowski & Lai (K-L) index
	Earthquake vulnerability mapping of Istanbul, Turkey (Shafapourtehrany et al. 2022)	Area under ROC curve (AUC), sensitivity (SST), specificity (SPF), root-mean-squared-error (RMSE), positive predictive value (PPV), and negative predictive value (NPV)
K-means	Earthquake Magnitude Prediction (Kamat and Kamath 2017; Yuan 2021)	Sum of squares error, Davies-Bouldin index, Calinski-Harabasz index, and silhouette coefficient
	Geophysical post-earthquake diagnosis (Mato and Toulkeridis 2017; Ramdani et al. 2015)	Silhouette value
	Classification of earthquakes in Indonesia (Muhajir and Sari 2018)	C-Index, Davies Bouldin Index, and Connectivity Index
	Earthquake Distribution Mapping (Malik et al. 2024)	Silhouette Score
	Spatiotemporal Seismicity Analysis and Hazard Assessment (Shang et al. 2018)	K-L index
	Identification and classification of different seismotectonic provinces with similar characteristics (Ansari et al. 2009)	Hyper-volume and density criteria
	Finding strong Earthquake Prone Areas (Gvishiani et al. 2013)	Compared with generalized fault map of Iran
Fuzzy Clustering	Determination of seismic sources in Azerbaijan region (Ansari et al. 2015)	Cluster quality index
	Associating earthquakes with faults (Nejad et al. 2021)	Generalized fault map of Iran
	Earthquake Magnitude Prediction (Mirrashid 2014)	Parameters R^2, MAE, and RMSE
	Determine sub-faults of large earthquakes (Xiaoshi and Zhenxiang 2012)	Faults already known on geological maps
	Earthquake zoning in a wider area of the Republic of Croatia (Scitovski 2018)	Obtained automatically without using indexes
Density Clustering	Automatic definition of major seismic sources (Georgoulas et al. 2013)	Results comparison with expert knowledge
	Identify earthquake hot spots with 3-dimensional analysis (Lei 2010)	Fitness values, rewards, and accuracy based on California Seismic Hazard Map
	Seismic zoning in Iran (Sabermahani and Frederiksen 2024)	Compared the outcomes with (Mirzaei et al. 1998) model as a standard for evaluation
	Indicating simple (burst-like) structure and complex multi-level (swarm-like) structure of clusters (Talebi et al. 2024)	Closeness and Out-degree Centralization indexes
Graph Network / Model	Declustering of instrumental earthquake catalogs (Lippiello et al. 2023)	Susceptibility of the similarity matrix
	Implications for seismic hazard (Zaccagnino et al. 2023b)	Global coefficient of variation of inter-event times, Cv
	Investigation of the Shallow Seismicity (Telesca et al. 2024; Talebi et al. 2024)	Mutual Information (IMI) and the Frobenius norm

Table 3 (continued)

Category	Purpose	Evaluation metric
Others	Estimating Background Seismicity (Seismicity Declustering)	TM Metric (Tiampo et al. 2007), Entropy (Nicholson et al. 2000), Allen Factor (Telesca et al. 2015a), Morisita index (Telesca et al. 2016), Schuster Spectrum (Ader and Avouac 2013), Correlation Metric (Zaliapin et al. 2008), NND (Talebi et al. 2024)

as they might fail to identify subtle clustering patterns or miss events outside the dense areas of the data. Furthermore, density-based methods may struggle when dealing with clusters of varying density, leading to either over- or under-clustering in heterogeneous seismic regions.

For graph/network-based clustering, employed in studies by Lippiello et al. (2023) and Zaccagnino et al. (2023b), Susceptibility of the similarity matrix, Global coefficient of variation of inter-event times (Cv), and Mutual Information (IMI) are used to assess the relationships between seismic events by modeling them as networks or graphs. These metrics are important because they can capture complex, non-linear interactions between events, which is essential for understanding the underlying processes of earthquake occurrences. The Susceptibility of the similarity matrix measures how sensitive the clustering results are to changes in the similarity criteria, while Cv and IMI quantify temporal and spatial patterns in the event sequences. A key limitation of these metrics, however, is that they may require a large amount of computational resources, especially when dealing with large seismic datasets, making them less feasible for real-time monitoring or large-scale studies.

Lastly, other metrics, such as TM Metric (Tiampo et al. 2007), Entropy (Nicholson et al. 2000), and Morisita Index (Telesca et al. 2016), are used for clustering and estimation of background seismicity. These metrics are valuable for analyzing the distribution and temporal patterns of seismic events, as they help to distinguish between background seismicity and aftershock sequences. However, they may not always be sensitive enough to identify smaller clusters or rare seismic events, especially when the background seismicity is complex, or the clustering is weak. Additionally, some metrics, like Morisita Index, might struggle to differentiate between similar clusters, leading to ambiguous interpretations.

6 Seismicity declustering

Seismicity Declustering is another contrasting approach like clustering, but here the focus is on obtaining the best possible estimate of background seismicity by removing the dependent events (aftershocks, foreshocks in clustered form triggered due to mainshock) from the earthquake catalogs. Seismicity associated with background events (non-clustered independent) is referred to as background seismicity, usually modeled as a time-stationary space-inhomogenous marked Poisson process. These events are generated due to secular, tectonic loading, and stress transients due to the regular tectonic motion of earth (Tsukakoshi and Shimazaki 2006; Cao et al. 1996).

This process of determining the background seismicity rate after identifying and removing clustered aftershocks is useful in seismic hazard assessment (McGinty 2001; Abdalzaher et al. 2020), development of clustering models (Talbi et al. 2013; Teng and Baker 2019), and prediction research (Si et al. 2020). Hazard analysis and modeling are mostly carried out by considering the independent set of events which means the catalog is free from foreshock-aftershocks sequences. However, this task is very challenging and complicated due to laking of formal definitions of dependent foreshock-aftershock events. The sections below describe traditional approaches first and later, focusing on soft computing approaches as well as evolutionary methods.

6.1 Traditional and mostly used approaches for declustering

The process of seismicity declustering is an ill-posed problem with a lot of challenges associated with it; therefore, a variety of declustering algorithms are proposed with different sets of assumptions, models, and hypotheses. This problem is aimed at a particular region of interest, targeting a specific research goal and objectives. Table 4 is a summary of state-of-the-art algorithms for seismicity declustering based on the mathematical approach taken by the algorithm. Each algorithm is listed along with its advantages (characteristic marks) and disadvantages. These marks highlight the strengths and weaknesses of each approach, helping users choose the most suitable algorithm for their specific needs. Some of the traditional and frequently used algorithms are highlighted as follows:

1. Space-time window-based approaches Initially, Gardner and Knopoff (Knopoff and Gardner 1972; Gardner and Knopoff 1974) developed a simple window-based approach to distinguish the mainshocks, backgrounds, and dependent foreshock-aftershocks present in an earthquake catalog. They have provided the magnitude-dependent space window with length L (in km) and time window (duration) T (in days) for each event accordingly:

$$\log L = a \times M + b \quad \text{and} \quad \log T = c \times M + d \tag{43}$$

Window parameters a, b, c, and d are precisely chosen for a studied catalog by observing the resultant outcome of the method. Initially, events are re-arranged in decreasing order of their magnitude, and then window size is determined from the first event (a potential mainshock). The largest event in each window is considered a mainshock, and events that lie in it are considered as foreshock-aftershocks, and outside of the window are treated as backgrounds. Based on the Chi-square test on the aftershock-depleted catalog for Southern California, they have reported that residual events (background seismicity) follow the characteristics of Poisson distribution. The available standard and alternative window sizes are mentioned in the supplementary material of this paper, taken from (Uhrhammer 1986), (van Stiphout et al. 2012), and (Wooddell and Abrahamson 2014). It was based on the data of Southern California from 1932 to 1971 by subjectively identifying aftershock sequences and considering rupture dimensions. The Mw 7.3 Kern County earthquake was the largest during the period. This method is frequently used for seismicity declustering due to its simple procedure and the availability of the code with the ZMAP toolbox. However, the window's length and duration do not follow an optimization procedure. Also, their parameter performs poorly in different tectonic regimes with the presence of more high-intensity mainshocks.

2. Link-based method In this method, events are analyzed in pairs, and they are linked in the form of clusters based on their space and time interaction zone as mentioned in Reasenberg's declustering method (Reasenberg 1985). The interaction zone in the spatial

Table 4 Summary of the state-of-art algorithms for seismicity declustering with comparative analysis

Category	Method Name with Reference	Advantages (Characteristics)	Disadvantages	Comparative Effectiveness / Suitability
ST-Window	Gardner and Knopoff window (Knopoff and Gardner 1972; Gardner and Knopoff 1974)	Simplicity and effectiveness in separating aftershocks from background seismicity	Highly sensitive to parameter choices	Effective for broad catalogs but requires parameter tuning for accuracy
	Uhrhammer (Uhrhammer 1986)	Simple space-time window method	Highly sensitive to parameters, requires fine-tuning	Suitable for large datasets, but may miss subtle aftershocks if parameters are not well-calibrated
	Gruenthal Window (van Stiphout et al. 2012)	Better smoothing in spatial domain	Unable to identify higher-order aftershocks	Best for regions with clear aftershock patterns but less effective in complex seismic areas
ST-Link	Reasenberg's method (Reasenberg 1985)	Probabilistic framework based on Omori's law space-time stress re-distribution	Parameter sensitivity and high computational complexity	Suitable for large events but computationally expensive for real-time use
	Molchan-Dmitrieva method (Molchan and Dmitrieva 1992)	Probabilistic framework with statistically sound separation	No explicit criterion for choosing the parameter's value	Flexible but requires expertise for parameter selection
	Single link analysis (Frohlich and Davis 1990; Davis and Frohlich 1991)	Magnitude-independent	Difficult to set parameters C & d_o in Eq. (15)	Effective in sparse catalogs, but challenging in dense regions
	Stochastic Declustering (Zhuang et al. 2002, 2004)	Probabilistic model with realistic representations of seismic activity	Risk of overfitting	Best for long-term studies, but may struggle with short-term forecasting
ETAS model	ROBERE (Llenos and Michael 2020)	Maximum-likelihood estimation incorporating uncertainty	Computationally complex	Excellent for regional hazard analysis but requires significant computational power
	ETAS with Frankel's Kernel (Jiang and Zhuang 2010)	Non-parametric estimation	Limited discussion on efficiency	Versatile but can degrade with sparse data
Non-ETAS	Model Independent SD (Marsan and Lengline 2008; Marsan and Lengliné 2010)	Independent of initial model parameter estimation	Piece-wise constant kernel, no prior parameterization	Good for exploratory analysis, but lacks robustness for predictions
	Gamma distribution + Long-likelihood (Hainzl et al. 2006)	Magnitude independent	Thinning required	Effective for large, homogeneous catalogs but less so for sparse data

Table 4 (continued)

Category	Method Name with Reference	Advantages (Characteristics)	Disadvantages	Comparative Effectiveness / Suitability
Inter Event Distribution	Sliding Window + COV (Bottiglieri et al. 2009)	Easy estimation	Hypo-center information not used	Simple to implement, but misses spatial context in dense regions
	IET distribution + Randomly shuffled Sequence (Batac and Kantz 2014)	Event relationship without pre-defined conditions	Considers both IETs & IEDs	Handles irregular events, but computationally expensive
	Correlation metric (Baiesi and Paczuski 2004a)	Simple metric in space-time-magnitude domain	Difficult to choose threshold and b-value	Quick analysis, but lacks precision in distinguishing aftershocks from background noise
	NND + Bimodal Distribution (Zaliapin et al. 2008; Zaliapin and Ben-Zion 2020, 2022)	Refined space-time-magnitude distance	Ignores overlap in bimodal distribution	Effective for larger catalogs, but misses small aftershock sequences
Nearest Neighbor Distance	Zaliapin and Ben-Zion (Zaliapin and Ben-Zion 2022)	Identifies swarms and handles edge effects	Requires knowledge of b-value	Useful in swarm-dominated regions, but b-value estimate is crucial
	MCMC approach (Bayliss et al. 2019)	Allows overlap of Weibull functions	Requires posterior and prior distributions	Flexible but computationally intensive for large catalogs
	SNN-IBD (Vijay and Nanda 2018)	Intensity-based grouping in space-time	Not suitable for variable cluster densities	Effective for well-clustered seismicity but struggles with varying densities
	TM metric+PSO (Cho et al. 2010)	Ergodicity concept for fitness function	Assumes effective ergodic periods, and slow convergence	Useful for optimization but requires fine-tuning for convergence
	TM metric + GWO (Vijay and Nanda 2017a, 2019a)	Fast convergence, suitable for different catalogs	Does not consider magnitude completeness	Efficient for large datasets but may miss events without magnitude completeness
Evolutionary algorithm	Binary MOCOA (Sharma and Nanda 2022)	Adaptable to various data types	Dependent on seismic parameters, statistical analysis is required	Flexible but needs careful parameter handling
	Binary NSGA-II (Sharma et al. 2021a)	Fast convergence, less complex	Sensitive to earthquake catalog	Effective in smaller datasets with clear trends, but less reliable with sparse data
	Tri-stage clustering (Nanda et al. 2013)	Single iteration, requires less computation	Assumes pre-defined mainshocks	Best for small, well-defined datasets with known mainshocks; limited in dynamic or noisy data

Table 4 (continued)

Category	Method Name with Reference	Advantages (Characteristics)	Disadvantages	Comparative Effectiveness / Suitability
K-means algo	Tetra-stage clustering (Vijay and Nanda 2017b)	Includes depth with space, time, and magnitude	Requires pre-identified mainshocks	Effective for multi-dimensional data, but depends on mainshock identification. Not ideal for noisy datasets
	Sliding Window + K-means (Vijay and Nanda 2022)	Simple, fast implementation	Centroid-dependent, not suitable for overlapping clusters	Suitable for well-separated clusters; struggles with overlapping or dynamic seismic events
	SOM + DB-SCAN (Sharma et al. 2022)	Captures complex spatio-temporal patterns	Limited adaptability to varying seismicity patterns	Good for complex patterns in dense datasets, but less adaptable to sparse or irregular events
Neural network	Random Forest (Aden-Antoniów et al. 2022)	Fast, adaptive with supervised learning	Trained on ETAS catalog only, assumes NND, not suitable for short space-time seismicity	Effective for large, structured datasets but less suitable for short-term or sparse data
	Probabilistic function + SOM (Septier et al. 2023)	Fewer assumptions, unsupervised AI for complex data	Needs additional features to reduce ambiguity in crisis events	Flexible for complex data, but needs extra features to handle crisis situations effectively
	Variable ϵ-DB-SCAN (Vijay and Nanda 2019c)	Dynamic radius with time	High computation complexity, parameter dependent	Best for time-varying densities, but computationally expensive and sensitive to parameters
Density-based	Weighted ST-DPC (Vijay and Nanda 2021)	Suitable for time-varying densities, fewer parameters	Large computation, sensitivity to parameters, scalability, limited handling of noise	Effective for time-varying data, but struggles with scalability and noise
	Weighted Kernel FCM + DPC (Sharma and Nanda 2023b)	Efficient at finding density peaks	Requires fine-tuning of hyperparameters, higher complexity with large data	Best for identifying density peaks in medium-sized data; computationally intense for large datasets
Fuzzy-based	FCM + DPC (Sharma et al. 2021b)	Automatically detects threshold values, handles irregular data	Dependency on distance metric, scalability issue	Suitable for complex datasets, but struggles with scalability and distance metric sensitivity
Filtering method	HMM (Wu 2010)	Better than ETAS for declustering	Assumes uniformity in earthquake proximity oversimplifies dynamics	Works for simple, predictable seismic events but oversimplifies complex spatiotemporal dynamics

domain is based on the stress around the mainshock, and Omori's law is used to define the time domain. The research focus of the paper was the identification of fore-and aftershocks in central California during 1969-1982 for events having $M \geq 4$. Similarly, the single-link cluster analysis (SLC) procedure links the event present in a catalog in a chain based on the length $(d < d_o)$ and then removes all the edges longer than d_o (Frohlich and Davis 1985). The result is to split the chain into isolated events and overlapping clusters. The optimal criterion for clustering is the shortest distance between any two events of different clusters (inter-cluster distance) are longer than the intra-cluster distance. In this method, *d* termed as ST-distance is calculated in the following way:

$$d^2 = |g_1 - g_2|^2 + C^2|t_1 - t_2|^2 \tag{44}$$

where earthquake is assumed to be a homogeneous space-time objects $x = (g, t)$ with $C = 1$ km/day and $d_o = 9.4$ (Frohlich and Davis 1990; Davis and Frohlich 1991). The method is illustrated on a global data set of 2178 earthquakes having $mb \geq 5.8$ during 1964-1986 reported in the International Seismological Centre (ISC), and sets of earthquakes having $m_b \geq 4.9$ occurring in Central America and in the Aleutians.

3. Stochastic declustering (SD) algorithm Instead of a deterministic approach, later on, Zhuang et al.. (Zhuang et al. 2002, 2004; Zhuang 2006) introduced a probabilistic declustering method that is based on the ETAS clustering model, reported in (Ogata 1988, 1999). Based on this model, background seismicity is estimated and separated from the clustered component in a probabilistic manner. Here, background seismicity is assumed to be a function of space and magnitude but not of time, along with clustering parameters associated with them. The thinning procedure is adopted for obtaining the probabilities of events to consider as background or aftershock (triggered event) and applied to decluster the earthquake data of New Zealand, Central, and Western Japan with magnitude $M_J \geq 4.0$. Recently, this model has been used in (Llenos and Michael 2020) to obtain the regionally optimized background earthquake rates for probabilistic seismic hazard assessment of induced seismicity in Oklahoma and Kansas and tectonic activity in the San Francisco Bay Region.

4. Model-independent stochastic declustering (MISD) Marsan and Lengline (Marsan and Lengline 2008; Marsan and Lengliné 2010) introduced model-independent stochastic declustering, by accepting any generalized seismicity model (other than ETAS as in (Zhuang et al. 2002). According to this, a event *e* with magnitude $m_e \in [m_i, m_{i+1}]$ and occurrence time t_e can trigger aftershocks at location *x* and time $t \geq t_e$ with following conditional intensity function:

$$\lambda_e(x, t) = \sum_j \sum_k \lambda_{ijk} \theta(t_j < t - t_e < t_{j+1}) \theta(r_k \leq r_e(x) < r_{k+1}) \tag{45}$$

where index *i*, *j*, and *k* represents magnitude, time and distance respectively for unknown λ_{ijk}. $r_e(x)$ is the 2D/3D distance between triggered event and the location *x*. Here, time interval and distance range are discretized in the conditional intensity function with a piecewise constant triggering kernel. The function unknowns are determined from the Expectation-Maximization (EM) algorithm by iterative computing the probabilities of earthquake occurrences.

5. Interevent time and distance-based Declustering In many studies, the coefficient of variation

$$COV = \frac{\sigma(\Delta t)}{\bar{\sigma}} \tag{46}$$

distribution based on inter-event time (IET Δt) or/both distance (IED Δr) between the successive pair of earthquakes is investigated to find a suitable way for declustering events in a given catalog. The IET vs. IED plot for the Himalaya earthquake catalog is shown in Fig. 8. It shows two different populations of earthquake catalogs for clustered and background seismicity. The clustered seismicity is located at lower values of both IET and IED, and the higher values represent the background seismicity of the earthquake events. Hainzl et al. (2006) argued that inter-event time is well-fitted by the Gamma distribution by assuming the Poissonian background activity and Omori law-based aftershock sequences. It is used as an independent and non-parametric maximum likelihood estimation of background rate. This method is illustrated for Southern California (1984-2002) with magnitude $m \geq 2.3$ based on the thinning procedure. Similarly, Bottiglieri et al. (2009) used the inter-event times and defined the coefficient for a given time series of earthquakes. Here σ is the standard deviation. This iterative method finds out the time interval for which COV is less than 1 and considers backgrounds in that period. Alternatively, the start time and the duration of the aftershock cluster sequence are precisely identified using the method. Batac and Kantz (2014) described a separation mechanism of two components of seismicity by defining the characteristic value Δr^*. It is obtained by comparing the original interevent distance distribution and obtained from randomly shuffled sequences. They have suggested that after $\Delta r > \Delta r^*$, the distributions of Δr follow similar behavior as randomly shuffled sequences and events are uncorrelated. This method does not use pre-defined conditions to find the relationships between successive events.

6. Nearest-Neighbor Distance algorithm Baiesi and Paczuski (Baiesi and Paczuski 2004b) introduced a space-time-magnitude-based correlation metric to find the correlation among the pair of earthquake events. It is defined as:

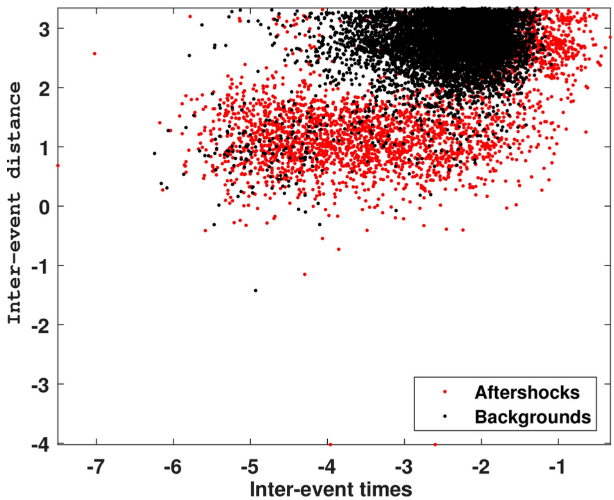


Fig. 8 Inter-event time vs inter-event distance (taken in log scale) that shows the two distinct EQ populations that occurred in the Himalayan region during 2001–2024

$$\eta_{ij} = t_{ij}.r_{ij}^{d_f}.10^{-b.M_i}, \forall t_{ij} = (t_j - t_i) > 0. \tag{47}$$

where η_{ij} distance between event *i* and $j > i$, based on the arrival time t_{ij}, 2D/3D-location $r_{ij} = |r_j - r_i|$, and magnitude M_i of an event. The tuning parameter d_f is the fractal dimension as per the epicenter distribution, and b is the G-R law's parameter. The η_j for earthquake *j* is determined by considering all the preceding events $i < j$, and then η_j^* is observed as minimum distance for which index $i = i^*$, and linking *j* with i^*. The backgrounds with $\eta_j^* > n_c$ and aftershocks with $\eta_j^* < \eta_c$ are identified by observing the distribution of η_j^* which has very wide response. $d_f = 1.6$ and $b = 1$ is the optimal choice for better results. Inspired from (Baiesi and Paczuski 2004b), Zaliapin et al.. (Zaliapin et al. 2008) redefined the Eq.(17) as nearest neighbor distance (NND) η_{ij} in terms of rescaled interevent distance R_{ij} and rescaled interevent time T_{ij} between events *i* and *j*:

$$T_{ij} = t_{ij}.10^{-b.M_i/2} \tag{48}$$

and space component

$$R_{ij} = (r_{ij})^{d_f}.10^{-b.M_i/2} \tag{49}$$

where M_i is the magnitude of the parent event *i*, and $\eta_{ij} = T_{ij} \times R_{ij}$. or equivalently $\log_{10} \eta_{ij} = \log_{10} T_{ij} + \log_{10} R_{ij}$. The joint 2D distribution of the nearest-neighbor pair (*T*, *R*) is used to distinguish two distinct populations of earthquakes (bimodal distribution). These two populations correspond to space-homogeneous, time-stationary Poissonian background activity and clustered aftershock sequences with smaller space-time inter-event distances. This method does not require the threshold η_c as used in (Baiesi and Paczuski 2004b). The more detailed procedure and improvement in it is found in Zaliapin and Ben-Zion (2011, 2013, 2022).

6.2 Recently introduced machine learning approaches

Apart from traditional methods, recent studies revealed interesting and potential ML frameworks for dealing with the problem of catalog declustering by considering appropriate assumptions, constraints, and case studies. Recently, several novel techniques have been incorporated to address the challenges posed by the complex and time-varying spatiotemporal dynamics of seismicity. Aden-Antoniów et al. (2022) developed an adaptable Random Forest classifier model for declustering the real earthquake catalogs. Initially, this model is trained on various synthetic catalogs generated by an ETAS model. Then, the trained model is applied to the relocated Southern California catalog from 1981 to 2019 and the New Zealand GeoNet catalog from 2010 to 2020. This model outperforms and improves the quality of the declustering in comparison with k-means, Gaussian-mixture model, support vector machine, and applications of the Nearest neighbor distance NND metrics. Pisarenko and Rodkin (2019) reported a generalized distance (GD) metric (window) by employing some assumptions on the NND method. In this method, the catalog is truncated from the end, and only the main shocks are used that occurred not later than a certain time limit, whereas, in the NND method, the catalog should be truncated from its beginning (from the earliest events). Wu (2010) developed a simple hidden Markov earthquake occurrence model

(HMM) for declustering seismicity in central and western regions of Japan from 1926 to 1995 with M $\geq$ 4.0 and a depth of less than 100 km. In this, a forward-backward algorithm is used to compute the conditional distribution and the likelihood function of the model, and a Viterbi algorithm is used to find the most likely hidden state sequence.

Nanda et al. (2013) proposed a tri-stage model based on the single-iteration-K means algorithm for declustering the catalogs of Indonesia, Japan, and California. In this, some high-magnitude events are considered cluster-centroids and do not change during the clustering procedure in each stage. This study is improved in Vijay and Nanda (2017b) by introducing a tetra-stage clustering model with the inclusion of depth in addition to occurrence time, location, and magnitude during the clustering procedure. Tetra-stage declustering model (Vijay and Nanda 2017b) efficiently identifies the spatial seismic zones obtained on the Himalaya catalog. Seven deadly earthquake epicenter locations are considered cluster centroids, and the entire region is divided into different seismic zones. Later, time-based k-means clustering is applied to decluster the seismic catalog. The declustered catalog is as shown in Fig. 9. The clustered seismic (aftershocks) activity is represented by blue dots. It is obvious from the Fig. 9 that events are closely located at the location of mainshock activity. Recently, some of the hybrid clustering mechanisms have also been reported in (Sharma et al. 2021b; Vijay and Nanda 2019b, c) to overcome the limitation of the K-means clustering algorithm for earthquake catalogs.

6.3 Nature-inspired optimization algorithms

In some studies, researchers also formulated the declustering problem in an optimization framework and applied a variety of nature-inspired algorithms for optimizing a formulated fitness function (Vijay and Nanda 2018). Vijay and Nanda (2019a) introduced the quantum version of the grey wolf optimizer and then applied it in optimizing the TM metric-based fitness function. The TM-metric was used for the ergodic-based analysis of the seismicity, and

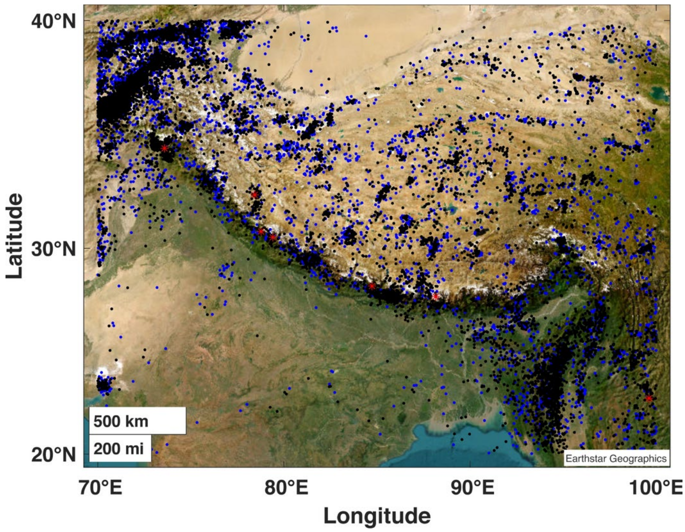


Fig. 9 Distribution of epicenters of clustered events (in black dots) and backgrounds (in blue dots) obtained from tetra stage declustering model (Vijay and Nanda 2017b) for Himalaya during 2001–2024

later on, it was used to quantify the earthquake clustering in Tiampo et al. (2003) and Cho et al. (2010). This study allows for determining the effective ergodic periods during which the occurrence of seismicity is considered random in both space and time, i.e., not in clustered form. They have also compared the algorithm performance with the PSO-based declustering model in (Cho et al. 2010). One recent approach developed by Sharma and Nanda (2022) to address the problem of seismicity declustering is through the application of single-objective Aquila optimization, which leverages the nearest neighbor distance to identify and separate seismic events into distinct clusters. This method focuses on optimizing the nearest neighbor distance, typically a proximity-based criterion, and is used as a threshold parameter to delineate seismic clusters in the catalog.

6.4 Multi and Many objective optimization algorithms

Sharma et al. (2021a) formulated the problem of seismicity declustering as binary multi-objective optimization and proposed a solution with the NSGA-II algorithm implemented using logical AND/OR operation. Later, Sharma and Nanda (2022) developed a multi-objective Chimp optimization and applied it to decluster an earthquake catalog by formulating it in a multi-objective framework. The hunting behavior of chimps is used to model the algorithm in a mathematical sense and to identify the statistical parameters of seismicity. In this context, space-time statistical parameters such as the m-Morisita $(m - MI)$ index and the Coefficient of Variance (COV) are incorporated into the optimization process, and optimal values are found, allowing for a more comprehensive assessment of seismic cluster separation. The optimal value is identified in terms of Pareto fronts. Taking this a step further, a more recent development in seismicity declustering involves the introduction of a many-objective Chimp optimization algorithm in which a reference-point-based mechanism is integrated with a fundamental Chimp optimization algorithm (Sharma and Nanda 2024).

This advanced approach simultaneously optimizes multiple statistical parameters in the space-time domain to determine optimal threshold values for the identification of seismic clusters. Four important statistical parameters, m-Morisita (Golay et al. 2014), Average nearest neighbor (ANN) (Sharma and Nanda 2024), Coefficient of Variance (COV) (Vijay and Nanda 2019b) and nearest neighbor distance (NND) (Baiesi and Paczuski 2005), are optimized simultaneously and results are obtained in terms of parallel Plot. Cumulative and Lambda (λ) plots are two important graphical parameters used to evaluate the accuracy of the declustering model. In the proposed manuscript, the seismic catalog of the Himalaya region is analyzed using a many-objective chimp optimization algorithm in terms of Cumulative and Lambda (λ) Plot. The cumulative Plot reported the total number of events that occurred within that period. λ-plot depicts the seismicity variation with time, and a sudden change in slope represents the high seismic activity at a specific duration. The clustered and background events obtained in terms of cumulative and λ-plot are depicted in Fig. 10, respectively. It is observed from the plots that background seismicity has linear and stationary characteristics with minor changes, representing that it can be fitted with the stationary Poisson process. The aftershocks have similar characteristics to the actual catalog in both the cumulative Plot and λ-plot, which reveals the accurate identification of seismic clusters (aftershocks) and backgrounds. Evolutionary-based studies for similar work are also reported in (Khare et al. 2019; Sharma et al. 2021a; Vijay and Nanda 2017a) to improve global convergence.

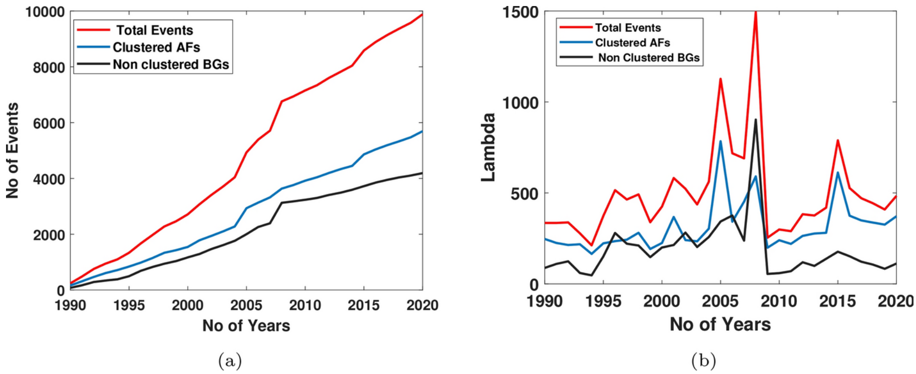


Fig. 10 **a** Cumulative plot and **b** λ-plot obtained for Himalaya region from Many-objective optimization method (Sharma and Nanda 2024)

6.5 Neural network based approaches

The state-of-the-art algorithms have made significant strides in handling large-scale seismic data and complex patterns. For instance, K-means clustering and neural network algorithms have been extended to account for temporal variations and varying spatial densities. Additionally, SOM, DBSCAN, and other clustering algorithms have been adapted to suit the needs of seismicity declustering. Sharma et al. (2022) developed a two-stage clustering approach comprising a Self-Organized Map and Density-based Temporal Clustering to identify significant aftershocks and independent background events. The event's location and depth information in the earthquake catalog is utilized to identify major hot spots (SOM prototypes) spatially, followed by density-based temporal clustering to decipher the neighborhood events of each SOM prototype. The Himalaya catalog is analyzed using the SOM-DBSCAN model, and results obtained for spatial zone identification are depicted in Fig. 11. It is observed from the Fig. 11 some earthquake events are hit many times when random information is put into the SOM represented by black dots. This is due to the high density of points in surrounding regions.

This spatiotemporal analysis effectively identifies aftershock clusters and background events of seven different seismically active regions. The traditional Self-Organizing Map (SOM) algorithm developed faces limitations in topological preservation and handling varying data densities due to a fixed learning rate. Later, the same authors modified the SOM algorithm to address these shortcomings and incorporated mean-shift clustering (Sharma and Nanda 2023a). This modified approach not only preserved the topological properties of the data but also enabled the identification of clusters with varying densities, overcoming the limitations of the traditional SOM. Alexandridis et al. (2013) developed a new method to estimate large earthquakes using a radial basis function (RBF) neural network. To train the neural networks, a powerful algorithm called fuzzy means training is used. However, this algorithm is modified to include a leave-one-out procedure. This helps account for the limited training data available, which is a common issue when trying to model earthquakes using data-driven techniques. Additionally, the proposed training method combines Reasenberg's clustering technique. This technique removes aftershock events from the earthquake data catalog before feeding the data into the neural network. This pre-processing step fur-

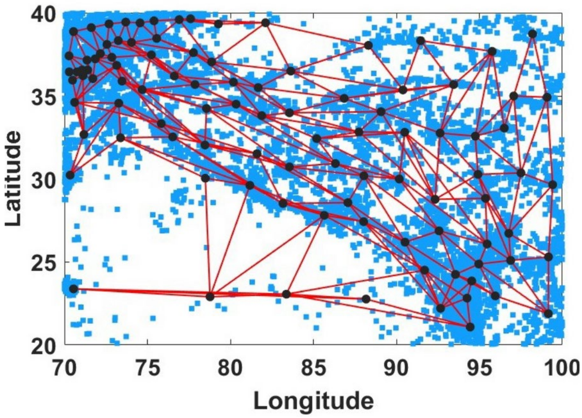


Fig. 11 SOM prototypes obtained from SOM-DBSCAN model (Sharma et al. 2022) for Himalaya catalog

ther improves the estimation accuracy. These algorithms are summarized in Table 4. To further enhance the accuracy and efficiency of the declustering process, machine learning, and deep learning techniques have been integrated. This includes the application of Hidden Markov Model and kernel FCM algorithms to account for the non-linear and non-Gaussian nature of seismicity data. However, despite these advancements, there remains room for improvement in the declustering algorithms. One potential avenue of exploration involves the incorporation of additional features, such as the presence of specific types of earthquakes, volcanic activity, and meteorite impacts, to enhance the accuracy of the clustering and classification process.

6.6 Stationarity and non-stationarity of background seismicity in seismicity declustering

The differentiation between stationary and non-stationary models in seismicity declustering is a pivotal aspect of seismic hazard assessment. The assumption of stationarity in background seismicity, where seismicity rates are considered constant over time and space, has long been a cornerstone in traditional declustering methods (Gardner and Knopoff 1974; Reasenberg 1985). However, recent advances have highlighted the complexities of non-stationarity, driven by both natural processes and anthropogenic activities (Zhuang et al. 2002). This section synthesizes findings from the past decade to provide a comprehensive understanding of this paradigm shift.

1. Traditional Stationary Models and Their Limitations: Foundational stationary models, such as those by Gardner and Knopoff (1974) and Reasenberg (1985)., were developed with the premise that background seismicity follows a Poissonian distribution. These models simplify seismic hazard assessments by providing computationally efficient methodologies, particularly suited for tectonically stable regions with minimal external influences (Zhuang et al. 2002). For instance, Gardner and Knopoff's spatial windowing method efficiently distinguishes aftershocks from background events, assuming that seismicity rates are constant over time (Zaliapin and Ben-Zion 2016). However, stationary models often fail to adapt to regions influenced by transient or dynamic factors, such as evolving stress fields and fault interactions. Studies have demonstrated that these models tend to misclassify triggered events in tectonically active regions (Zaliapin and Ben-Zion 2016). Even extensions like the Epidemic-Type Aftershock Sequence (ETAS) model-despite introducing time-dependent parameters-remain limited in fully capturing variations in seismicity caused by external influences (Zhuang et al. 2002). Stationary models are computationally efficient and effective for regions with minimal external influences. However, they often fail to adapt to temporal and spatial variability, leading to potential misclassification of events and underestimation of hazard levels in dynamic environments.

2. Non-Stationarity in Background Seismicity: The Poisson process assumes that earthquake occurrences are independent and follow a constant average rate. This assumption simplifies the modeling and prediction of seismic events. Recent studies emphasize that background seismicity is inherently non-stationary, shaped by long-term tectonic processes, transient stress perturbations, and anthropogenic activities. Non-stationary seismicity implies that the rate of earthquake occurrences is not constant but varies over time. This violates the fundamental assumption of a Poisson process, which requires a constant rate Reyes Canales and van der Baan (2019). Non-stationary processes can also introduce dependencies between events. For example, periods of high seismic activity may be followed by periods of low activity, indicating a correlation between events. This contradicts the Poisson process assumption of independent events Olszewska et al. (2017). Non-stationarity also affects probabilistic seismic hazard analysis (PSHA). Traditional PSHA methods, which assume stationarity, may underestimate or overestimate the hazard if the temporal variations in seismicity are not accounted for. Incorporating non-stationary models can provide more accurate hazard assessments by considering time-dependent changes in earthquake rates Reyes Canales and van der Baan (2019).

To address non-stationarity, alternative models such as the non-homogeneous Poisson process (NHPP) and epidemic-type aftershock sequence (ETAS) models have been developed Ma and Whitt (2016); Zhuang et al. (2002). These models allow for time-varying rates and can incorporate the effects of both natural and induced seismicity. For example, the ETAS model can account for aftershocks and other time-dependent seismicity patterns, providing a more realistic representation of earthquake occurrences.

7 Importance and application of aftershocks in seismology: spatiotemporal earthquake data mining

7.1 Importance of aftershocks in seismology

Aftershocks are crucial in advancing the understanding of seismology, contributing valuable insights into the complex dynamics of earthquake sequences (Wiens et al. 1994). These secondary seismic events, occurring in the aftermath of a major earthquake, provide a unique opportunity to study the aftershock sequence and unravel the underlying geological processes. In some instances, a strong aftershock can cause more damage than the mainshock, leading to an underestimation of the seismic hazard of some areas. For instance, the aftershocks following the 1976 M7.8 Tangshan earthquake in China caused more damage than the mainshock, leading to additional casualties and property losses (Wu et al. 2024). Understanding aftershocks is vital for seismic hazard assessment, as they can pose significant threats to affected regions, compounding the impact of the initial earthquake (Asad et al. 2023). Moreover, aftershocks offer essential data for refining earthquake forecasting models and improving the ability to assess the likelihood of subsequent seismic events (Vere-Jones 1995). The study of aftershocks also aids in characterizing fault behavior and the mechanical properties of Earth's crust, shedding light on the factors influencing seismic activity (Brodsky et al. 2020). Therefore, investigating the importance of aftershocks in seismology is fundamental not only for deciphering the aftermath of earthquakes but also for enhancing the ability to mitigate seismic risks and safeguard vulnerable communities.

7.2 Performance evaluation and loss assessment before and after mainshock-aftershock earthquake sequences

Performance evaluation and loss assessment before and after mainshock-aftershock earthquake sequences are crucial aspects of seismic risk analysis (Wen et al. 2017). Before the occurrence of a seismic event, assessing the vulnerability of structures and infrastructure is paramount for disaster preparedness (Duzgun et al. 2011). Understanding the potential impact and vulnerabilities allows for the implementation of effective mitigation measures. After a mainshock, the evaluation of performance and loss helps gauge the effectiveness of existing infrastructure and emergency response systems. This assessment provides valuable data for refining seismic design standards and updating building codes to enhance resilience. The study of aftershock sequences is particularly important, as these secondary seismic events can lead to additional damage and complicate recovery efforts. By analyzing performance and loss data both before and after earthquake sequences, researchers and policymakers can develop more informed strategies for mitigating the impact of seismic events and improving overall resilience in earthquake-prone regions (Freddi et al. 2021). The aftershock identifications help to define aftershock zones, fault dimensions, aftershock area expansion, seismicity gap, relations between fault size, and other source parameters. Without knowing this, it is very difficult to make ground motion predictions for constructing earthquake-resistant structures. Earthquake modeling, forecasting, prediction, and estimation are carried out based on the investigation of aftershock productivity in space, time, and magnitude levels.

7.3 Clustering algorithms real-life applications in seismology

Nowadays, AI studies are highly demanding, with a long-term goal of making quantitative probabilistic forecasts of future earthquake occurrences instead of deterministic earthquake prediction. Several researchers are targeting forecasts of aftershock locations with the help of ML/DL-based schemes (Beroza 2018) for aftershock identification (clustering), and its separation from background activity (declustering) is a critical yet highly challenging task. By various estimates, the aftershocks contribute about 30-40 percent to the total number of earthquakes in world catalogs and contain significant information on rupture processes. The more easily identifiable aftershocks are earlier aftershocks of large earthquakes in the near zone, i.e., where the rate of aftershock occurrence per unit of time and space significantly exceeds the background rate. Otherwise, the identification of aftershocks is hampered by background seismicity and by overlapping aftershock sequences. The absence of a physical concept of later aftershocks is the main difficulty for aftershock separation. Under these circumstances, a great number of aftershock identification techniques have existed for many years. Seismic clustering is a technique used in geophysics and seismology to group seismic events based on their similarities.

Seismic clustering is often performed using various algorithms, Artificial Intelligence techniques, Machine learning, and Deep Learning models. Artificial Intelligence (AI) plays a crucial role in seismic clustering by providing advanced techniques for data analysis, pattern recognition, and decision-making and prediction. Clustering allows for the identification of different earthquake sources or faults, helping to understand the seismicity patterns in a region. Over the years, researchers have developed several clustering models based on different algorithms. Weatherill and Burton (2009) used a K-means clustering approach to identify the shallow seismic source zones in the Aegean region. Zaliapin and Ben-Zion (2013) used an NND approach for comprehensive detection and analysis of earthquake clusters in the California region. Ouillon and Sornette (2011) proposed the Gaussian mixture approach implemented in an expectation maximization (EM) procedure. A cross-validation scheme is then used to determine the number of kernels, which provides an optimal data clustering of the catalog. Clustering also helps in distinguishing between natural earthquakes and human-induced seismic events, such as those caused by mining activities or hydraulic fracturing (Zaliapin and Ben-Zion 2016; Silva et al. 2021). Seismic clustering can reveal the spatial and temporal evolution of earthquake sequences, which is crucial for assessing seismic hazards and potential aftershock occurrences (Leśniak and Isakow 2009; Yang et al. 2019). Clustering techniques are also used to discriminate different types of seismic events, such as earthquakes, explosions, and mining-induced events, based on their waveform characteristics (Duan et al. 2021; Hudyma 2008). Seismic clustering can be used to improve the accuracy of seismic tomography, a technique that maps the earth's interior structure using seismic waves (Braeuer and Bauer 2015). By identifying and separating different seismic event clusters, tomographic models can better account for variations in wave propagation paths and velocities, leading to more accurate subsurface imaging (Di Giuseppe et al. 2014; Eymold and Jordan 2019). In the oil and gas industry, seismic clustering is employed to monitor and characterize subsurface reservoirs during exploration and production activities (Yang et al. 2021; Maas et al. 2023; Ali et al. 2023). Clustering can identify different types of seismic events, such as those related to fluid movement or fracture propagation, providing valuable information for reservoir management and enhanced recovery techniques. Seismic clustering is widely used in microseismic monitoring, which involves detecting and locating small-scale seismic events associated with fracturing processes in reservoirs or mining operations (Anikiev et al. 2023; Duan et al. 2021).

8 Conclusion and future work

This paper has provided a comprehensive review of spatiotemporal seismicity analysis using clustering techniques, highlighting their significance in understanding earthquake patterns, identifying aftershock sequences, and improving seismic hazard assessments. Clustering methods have been instrumental in analyzing seismic data by grouping earthquakes based on spatial and temporal proximity, revealing underlying geophysical processes. However, despite notable advancements, several unresolved challenges persist, necessitating further research and methodological improvements. The major challenges and unresolved issues are

- **Challenges in Traditional Clustering Methods:** Traditional algorithms such as K-means, DBSCAN, and hierarchical clustering struggle to capture the complex, nonlinear relationships inherent in earthquake occurrence. Their performance is susceptible to parameter choices, and they often fail to incorporate physical constraints such as fault structures and tectonic activity.
- **Limitations of Model-Based Approaches:** Statistical models like the Epidemic-Type Aftershock Sequence (ETAS) and Kernel Density Estimation (KDE)-based clustering require extensive parameter tuning and often assume stationarity of background seismicity, which may not always be realistic. Moreover, their computational complexity makes them less suitable for large datasets.
- **Machine Learning and Deep Learning Challenges:** While machine learning approaches (e.g., self-organizing maps, support vector machines) and deep learning models (e.g., CNNs, LSTMs) offer enhanced clustering accuracy, they require large labeled datasets, which are often scarce in seismology. Additionally, deep learning methods lack interpretability, limiting their validation against physical earthquake processes.
- **Real-Time Clustering and Data Integration Issues:** Current methods struggle with computational inefficiencies in real-time applications. Additionally, the lack of standardized seismic databases and the difficulty in integrating multi-source data (e.g., satellite imagery and geodetic measurements) hinder collaborative research efforts.

Different clustering techniques vary in effectiveness based on the dataset characteristics and research objectives. The relationships between the existing methods and comparative effectiveness are

- **Traditional clustering methods** (e.g., K-means, DBSCAN) are useful for exploratory analysis but have limitations in capturing complex earthquake interactions.
- **Model-based approaches** (e.g., ETAS, KDE clustering) provide a stronger physical basis for aftershock clustering but require high computational resources.
- **Machine learning-based methods** perform well on large datasets but face issues related to data availability and interpretability.
- **Hybrid models** that integrate physics-based constraints with data-driven approaches offer promising improvements in accuracy and adaptability.

To overcome existing challenges and enhance spatiotemporal seismicity analysis, future research should focus on the following key directions.

- **Development of Hybrid Clustering Models:** Future research should integrate physics-based models (e.g., ETAS) with machine learning techniques to improve clustering accuracy while maintaining interpretability.
- **Advancements in Real-Time Clustering:** High-speed, adaptive algorithms should be developed for real-time seismic data analysis, utilizing edge computing and cloud-based solutions.
- **Uncertainty Quantification and Model Validation:** Statistical methods for uncertainty estimation should be explored alongside investigations into the stationarity of background seismicity.
- **Integration of Multi-Source Data:** Combining seismic data with geological, satellite,

and geophysical observations will enhance clustering robustness. Machine learning techniques for multi-modal data fusion should be developed.

- **Establishment of Open Data and Collaborative Frameworks:** Strengthening international collaborations through open-access seismic databases and standardized methodologies will foster more comprehensive clustering studies.
- **Improvement of Visualization and Decision-Support Tools:** User-friendly software and interactive dashboards should be developed to facilitate the interpretation of clustering results for researchers and policymakers.

Spatiotemporal seismicity analysis using clustering techniques remains a rapidly evolving field with significant implications for earthquake hazard assessment and disaster risk management. While existing methods provide valuable insights, challenges related to parameter sensitivity, computational efficiency, and data integration persist. Leveraging advancements in machine learning, high-performance computing, and real-time data analytics will lead to more adaptive, interpretable, and scalable clustering methods for seismic analysis. Addressing these challenges will contribute to more effective earthquake forecasting, improved seismic risk assessment, and, ultimately, the development of safer and more resilient communities in earthquake-prone regions.

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Declarations

Conflict of interest The authors declare that there is no Conflict of interest.

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