

How Much Temporal Information Does Earthquake Declustering Remove? An Entropy-Based Analysis of the Türkiye Catalogue

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Research Article

Keywords:

Posted Date: October 13th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11058268/v1>

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Abstract

Earthquake catalogues contain spatial and temporal clustering generated primarily by foreshock-aftershock sequences, which can obscure the underlying structure of background seismic activity. Declustering is therefore commonly applied before statistical analyses intended to characterize independent seismicity. However, the dependence associated with clustered events also represents an embedded feature of earthquake activity that can be quantified using appropriate statistical measures. Information-theoretic methods provide an objective framework for evaluating this temporal organization and the extent to which it remains after declustering.

Within this context, this study examines the uncertainty and short-term temporal predictability of monthly earthquake activity in Türkiye using catalogues declustered by the Gardner-Knopoff, Deniz-Yüçemen, and Reasenberg methods. Monthly event counts were classified into catalogue-specific activity states and analysed using Shannon entropy, conditional entropy, lagged mutual information, moving-window analysis, and permutation testing. The Gardner-Knopoff and Deniz-Yüçemen catalogues exhibited weak and statistically non-significant month-to-month dependence, whereas the Reasenberg catalogue retained significant temporal organization during the early and recent periods. The findings demonstrate that the apparent predictability of seismic activity depends strongly on catalogue preparation. More broadly, information-theoretic measures provide a quantitative basis for comparing declustering algorithms according to the amount of temporal dependence they remove or retain.

1. Introduction

Earthquake occurrence is a central concern in seismic-hazard assessment, yet reliable deterministic prediction of an individual event's time, location, and magnitude remains beyond current scientific capability (Geller et al., 1997; Jordan et al., 2011; Mulargia et al., 2017). Contemporary catalogue-based approaches therefore emphasize probabilistic forecasting and the evaluation of how much information past seismicity provides about future activity (Jordan et al., 2011). A statistically detectable dependence between successive observations does not, by itself, constitute a deterministic precursor or an operational prediction rule; rather, it indicates temporal organization in the observed process.

Earthquake catalogues display pronounced spatial and temporal clustering because earthquakes can trigger subsequent events over a range of times and distances (Gardner & Knopoff, 1974; Reasenberg, 1985; Ogata, 1988). Foreshock–aftershock sequences may dominate short-term variations in event rates, whereas changes in detection capability, magnitude reporting, and catalogue completeness can generate apparent temporal variations unrelated to the underlying seismic process (Zuniga & Wyss, 1995; Woessner & Wiemer, 2005). Declustering is therefore commonly applied when the objective is to characterize background seismicity and retained main shocks. However, declustering algorithms employ different assumptions and classification rules and may consequently remove substantially different numbers of events and retain different levels of temporal dependence (Teng & Baker, 2019; Zaliapin &

Ben-Zion, 2020). This methodological sensitivity must therefore be considered when temporal organization or predictability is inferred from a declustered catalogue.

Information theory provides an appropriate framework for evaluating relative performances of these declustering algorithms. Shannon entropy measures uncertainty in the distribution of discrete activity states, whereas conditional entropy measures the uncertainty remaining in a future state when the present state is known. Mutual information quantifies the reduction in uncertainty provided by knowledge of the present state and does not require a linear relationship between variables (Shannon, 1948; Cover & Thomas, 2006; DelSole & Tippet, 2007; Young et al., 2023). When applied to a regular monthly sequence, lagged mutual information indicates whether the activity class observed in one month provides information about the following month or at longer temporal separations (Runge et al., 2019). These measures can therefore be used not only to characterize temporal organization in seismic activity but also to compare how much dependence remains after applying different declustering procedures.

Entropy-based approaches have a long history in seismology. Early studies used the principle of maximum entropy and information-theoretic arguments to investigate earthquake magnitude distributions and the Gutenberg–Richter frequency–magnitude relation (Shen & Mansinha, 1983; Main & Burton, 1984). More recent applications include configurational-entropy analysis of critical seismic populations and its potential relevance to catalogue declustering (Goltz, 2002), as well as Shannon-entropy analysis (Telesca et al., 2004). Subsequent studies related entropy to the Gutenberg–Richter distribution and seismic-sequence evolution (De Santis et al., 2011), examined spatial heterogeneity through wavelet entropy in Chilean earthquake catalogues (Nicolis & Mateu, 2015), and evaluated the spatio-temporal evolution of seismic populations (Bressan et al., 2017). More recent research has extended entropy-based analysis to earthquake nowcasting, regional seismic hazard characterization, and stochastic catalogue simulations (Rundle et al., 2019; Vogel et al., 2020; Posadas et al., 2023; Rundle et al., 2024). However, these studies generally focus on event magnitudes, interevent properties, spatial patterns, natural-time constructs, or catalogue-wide state variables. A direct assessment of the temporal information transmitted between successive monthly classes of declustered seismic activity has received comparatively limited attention. Moreover, to our knowledge, the long-term stability of this quantity has not been evaluated using a homogenized catalogue spanning the whole of Türkiye.

Entropy-based approaches have also been applied to Turkish seismicity. Kadılar et al. (2022) characterized earthquakes in the Aegean region of Türkiye using Shannon entropy, whereas Karakaş and Çalık (2020) examined earthquake volatility through several entropy measures. In a related probabilistic framework, Ünal and Çelebioğlu (2011) used a maximum-entropy Markov-chain model to investigate seismic hazard in Türkiye. More recently, Pastén et al. (2025) compared Shannon entropy, Tsallis entropy, and mutability for the 2023 Türkiye–Syria earthquake sequence. However, these studies did not evaluate the lagged mutual information and permutation-based month-to-month predictability of declustered national seismic activity considered here.

Accordingly, this study examines the temporal regularity of declustered earthquake activity in Türkiye using a homogenized seismic catalogue. Monthly activity is represented by discrete seismicity states, and information-theoretic measures are used to quantify both the overall uncertainty of these states and the information transmitted between successive months. The analysis evaluates temporal behavior across independent periods, considers dependence over multiple time lags, and examines its evolution through moving windows. Randomization-based tests are further used to distinguish observed temporal structure from finite-sample effects.

2. Data Preparation

The earthquake catalogue used in this study covers the region bounded by 26°–45°E and 35°–42°N, encompassing Türkiye and its immediate surrounding seismically active areas. Earthquake locations and active fault traces within the study region are shown in Fig. 1. The catalogue spans the period from January 1976 to December 2025. Magnitudes were expressed in moment magnitude, M_w , using the homogenized catalogue compiled from the magnitude-conversion relationships of Ulusay et al. (2004) and Akkar et al. (2010).

The original catalogue was declustered using three alternative methods: Gardner and Knopoff (1974), Deniz and Yüçemen (2000), and Reasenberg (1985). This procedure reduced the influence of foreshock-aftershock sequences on the temporal activity series. Magnitude-dependent time-distance criteria were applied separately under each method, and only independent events and retained main shocks were used in the subsequent analyses. As summarized in Table 1, the three methods identified markedly different numbers of dependent events. Gardner-Knopoff produced the largest reduction of the original catalogue, followed by Deniz-Yüçemen. Reasenberg was substantially less conservative and retained most of the events. These differences provide the basis for examining how declustering affects the temporal information remaining in the catalogue.

Table 1
Comparison of event removal and retention under the three declustering methods.

	Total Events	Identified clusters	Removed dependent events		Retained single events/main shocks	
			#	%	#	%
Gardner and Knopoff, 1974	39,950	3,098	29,160	73.00	10,790	27.00
Deniz and Yüçemen, 1999	39,950	2,940	27,986	70.05	11,964	29.95
Reasenberg, 1985	39,950	2,525	12,819	32.09	27,131	67.91

The magnitude of completeness (M_c) was estimated separately for the three declustered catalogues using the maximum-curvature method with a magnitude-bin width of 0.1. Figure 2 presents the temporal evolution of the cumulative magnitude of completeness for the three declustered catalogues. Although

the estimates fluctuate during the early years because of the limited number of recorded events, they converge rapidly as the cumulative sample size increases. The Gardner–Knopoff and Reasenbergs catalogues stabilize at approximately ($M_c=3.8$) by the late 1970s. The Deniz–Yüçemen catalogue exhibits minor subsequent fluctuations between 3.8 and 3.9 before stabilizing at 3.8. The close agreement among the three catalogues indicates that the completeness estimate is largely insensitive to the selected declustering method. To accommodate the minor fluctuations and apply a uniform criterion, a common threshold of ($M_w \geq 3.9$) was adopted for all subsequent analyses.

Figure 3 presents the monthly earthquake-count series obtained from the three declustered catalogues using the common completeness threshold of $M_w \geq 3.9$. The Gardner–Knopoff and Deniz–Yüçemen catalogues exhibit broadly similar temporal patterns. Their close agreement indicates that these two window-based methods produce comparable representations of background seismic activity. Although occasional peaks occur, particularly near the beginning and end of the study period, monthly activity generally fluctuates within a relatively narrow range.

The Reasenbergs catalogue retains substantially more events per month. Its temporal series also contains several pronounced peaks, most notably near the end of the study period. These peaks indicate that Reasenbergs declustering preserves a larger proportion of temporally concentrated events than the Gardner–Knopoff and Deniz–Yüçemen. Consequently, the estimated entropy and temporal dependence may be sensitive to the declustering procedure, particularly during periods of intense seismic activity. This difference provides the principal basis for evaluating the robustness of the entropy results across the three catalogues.

3. Methods

Information-theoretic measures were used to quantify the overall uncertainty and short-term temporal predictability of declustered monthly earthquake activity in Türkiye. Within this framework, information is interpreted as a reduction in uncertainty. Shannon entropy describes the uncertainty in the distribution of monthly activity states; conditional entropy measures the uncertainty remaining in the next month when the current activity state is known; and lagged mutual information quantifies the information transferred between activity states at different temporal separations. The analysis therefore evaluates statistical regularity in the catalogue-based activity series and does not constitute deterministic earthquake prediction.

Three declustering methods were selected to represent contrasting yet widely used approaches to dependent-event identification. Gardner–Knopoff is a conventional window-based method extensively used in seismic-hazard studies, whereas Deniz–Yüçemen provides a regional adaptation of magnitude-dependent time–distance windows developed for earthquake catalogues in Türkiye. Reasenbergs represents a conceptually different, interaction-based approach in which clusters evolve through event-to-event spatial and temporal associations. The comparison therefore includes a widely adopted global window method, a regionally calibrated window method, and a link-based clustering algorithm. The

objective was not to provide an exhaustive benchmark of all available declustering techniques, but to determine whether the temporal information inferred from the same catalogue remains robust across these contrasting and practically relevant procedures.

The inputs were three monthly event-count series derived from the Gardner-Knopoff, Deniz-Yucemen, and Reasenbergl declustered catalogues. Each catalogue was analysed independently. Events were aggregated from January 1976 through December 2025, producing three regular sequences of 600 calendar months, including months with zero events.

For entropy estimation, monthly event counts were converted into four discrete activity states using empirical quartiles calculated separately from the complete 1976–2025 record of each declustered catalogue. The states represent low, moderately low, moderately high, and high monthly seismic activity within the corresponding catalogue. Let N_t denote the monthly event count and let q_1 , q_2 , and q_3 denote the catalogue-specific global quartile thresholds. The discrete activity state S_t was defined as follows:

$$S_t = \begin{cases} S_1, & N_t \leq q_1 \\ S_2, & q_1 < N_t \leq q_2 \\ S_3, & q_2 < N_t \leq q_3 \\ S_4, & N_t > q_3 \end{cases}$$

1

The four-state classification provides sufficient resolution to distinguish activity levels while retaining enough observations for transition-probability estimation. For four equiprobable states, the theoretical maximum entropy is 2 bits. Because monthly counts are discrete, tied values at the quartile thresholds can occur and the observed state frequencies need not be exactly equal. Fewer states would merge potentially distinct activity levels, whereas more states would increase the number of transition-matrix cells and make period-specific probability estimates more sensitive to finite-sample effects. Within each catalogue, the same three global thresholds were retained for all periods and moving windows to ensure temporal comparability. Thresholds were not imposed across catalogues because the three declustering methods retained markedly different monthly event-count distributions.

The general uncertainty of the monthly activity-state distribution was quantified with Shannon entropy. For $K = 4$ possible states and state probability $p(s_i)$, Shannon entropy was calculated as:

$$H(S) = -\sum_{i=1}^K p(s_i) \log_2 p(s_i)$$

2

Shannon entropy summarizes the marginal distribution of activity states but does not account for their temporal order. To assess this dependence, conditional entropy was calculated. Conditional entropy measures the remaining uncertainty about the state of the following month when the earthquake-activity

state of the current month is known. Dependence between consecutive months was therefore assessed with conditional entropy:

$$H(S_{t+1} | S_t) = -\sum_{s_t} \sum_{s_{t+1}} p(s_t, s_{t+1}) \log_2 p(s_{t+1} | s_t)$$

3

Here, $p(s_i, s_j)$ is the joint probability of observing state s_i followed by state s_j , and $p(s_j | s_i)$ is the associated conditional transition probability. Conditional entropy close to Shannon entropy indicates that knowing the present activity state produces little reduction in uncertainty about the next month. Lower conditional entropy indicates a more ordered month-to-month sequence. The information supplied by the current month about the next month was quantified using mutual information:

$$I(S_t; S_{t+1}) = H(S_{t+1}) - H(S_{t+1} | S_t)$$

4

A normalized predictability index was also calculated to express the relative reduction in uncertainty:

$$PI = I(S_t; S_{t+1}) / H(S_{t+1})$$

5

The index approaches zero when the present state provides little information about the next state and approaches one when uncertainty in the next state is strongly reduced. It was used as a descriptive measure; statistical inference was based on mutual information and permutation testing.

To examine temporal variation, each 600-month catalogue series was divided into three non-overlapping periods of exactly 200 months: January 1976-August 1992, September 1992-April 2009, and May 2009-December 2025. The equal-length and non-overlapping design supports direct comparison of estimated probabilities and information measures without repeated observations. Shannon entropy, conditional entropy, one-month mutual information, and the normalized predictability index were calculated separately for every catalogue-period combination.

Lagged mutual information was subsequently calculated for lags from 1 to 12 months:

$$I_l = \sum_{i,j} p_{ij}^{(l)} \log_2 [p_{ij}^{(l)} / (p_i^{(0)} p_j^{(0)})]$$

6

Here, $p_{ij}^{(l)}$ is the joint probability that activity states i and j are separated by l months. Only observation pairs separated by exactly l months were used. Lag 1 represents short-term month-to-month dependence, whereas longer lags assess whether information persists beyond consecutive months.

Because examining multiple lags increases the chance of local excursions, lagged results beyond lag 1 were interpreted descriptively and were not assigned separate significance claims.

The temporal evolution of lag-1 mutual information was also described separately for each catalogue using 20-year moving windows advanced in two-year steps. The first window covered 1976–1995 and the final window covered 2006–2025. Each window contained 240 monthly observations and used the fixed global thresholds of its own catalogue. Mutual information was assigned to the centre year of each window. The 20-year window length balances temporal resolution with the number of observations required for stable state and transition-probability estimates. Because adjacent windows overlap substantially, the moving-window results were interpreted as descriptive time-evolution series rather than as independent tests.

The statistical significance of lag-1 mutual information was assessed separately for each of the nine catalogue-period combinations using 5,000 permutations. Within each combination, the monthly activity states were randomly reordered. This procedure preserves the marginal state frequencies of the relevant catalogue and period while removing temporal order. The empirical p value was computed as:

$$p = [1 + \sum_{b=1}^B 1(I_b \geq I_{obs})] / (B + 1)$$

7

Here, B is the number of permutations, I_b is the mutual information calculated from permutation b, I_{obs} is the observed mutual information, and the indicator function equals one when $I_b \geq I_{obs}$. Statistical significance was evaluated at $p < 0.05$. Because nine catalogue-period tests were examined, significant findings were additionally compared with a conservative Bonferroni threshold of $0.05/9 = 0.0056$. The mean permuted mutual information was retained to quantify the finite-sample contribution expected under the null hypothesis. A negative bias-corrected value does not represent negative information; it indicates that the observed value is below the average obtained from randomized sequences. Each test assesses temporal ordering within one catalogue and period and does not directly test differences among declustering methods or periods.

All analyses were implemented in MATLAB R2018. Entropy and mutual-information values were calculated with base-2 logarithms and are reported in bits. Terms associated with zero probabilities were omitted from summations, consistent with the limiting value $p \log_2 p = 0$.

4. Analysis and Results

The three declustered catalogues were analysed independently using catalogue-specific global quartiles. This approach retained a common four-state information framework while allowing for the substantially different monthly activity levels produced by the declustering methods. The quartile thresholds were 5, 6, and 8 events per month for Gardner-Knopoff; 5, 7, and 9 for Deniz-Yucemen; and 8, 12, and 15 for

Reasenber (Table 2). Because monthly counts are discrete, ties at the thresholds prevented the four states from being exactly equiprobable.

Table 2
Catalogue-specific empirical-quartile thresholds and global frequencies of monthly seismic-activity states.

Catalogue	State	Definition	n	%
GK	D1 Low	$N \leq 5$	217	36.2
GK	D2 Moderately low	$5 < N \leq 6$	102	17.0
GK	D3 Moderately high	$6 < N \leq 8$	145	24.2
GK	D4 High	$N > 8$	136	22.7
DY	D1 Low	$N \leq 5$	174	29.0
DY	D2 Moderately low	$5 < N \leq 7$	166	27.7
DY	D3 Moderately high	$7 < N \leq 9$	133	22.2
DY	D4 High	$N > 9$	127	21.2
Reas.	D1 Low	$N \leq 8$	168	28.0
Reas.	D2 Moderately low	$8 < N \leq 12$	174	29.0
Reas.	D3 Moderately high	$12 < N \leq 15$	120	20.0
Reas.	D4 High	$N > 15$	138	23.0

The period-specific state frequencies also differed by declustering method (Table 3). The Gardner-Knopoff series was weighed toward low activity in the first and final periods, whereas its middle period contained the largest share of high-activity months. Deniz-Yucemen showed a similar shift, although its state distribution was more balanced in the first two periods. Reasenber retained a comparatively large high-state share in both the first and final periods. These differences describe changes in marginal activity levels and do not, by themselves, demonstrate temporal predictability.

Table 3
Frequency Distribution of the Four Monthly Seismic-Activity States in The Independent
200-Month Periods, n (%).

Catalogue	Period	D1	D2	D3	D4
GK	1976-01 to 1992-08	84 (42.0)	33 (16.5)	46 (23.0)	37 (18.5)
GK	1992-09 to 2009-04	55 (27.5)	25 (12.5)	56 (28.0)	64 (32.0)
GK	2009-05 to 2025-12	78 (39.0)	44 (22.0)	43 (21.5)	35 (17.5)
DY	1976-01 to 1992-08	61 (30.5)	55 (27.5)	43 (21.5)	41 (20.5)
DY	1992-09 to 2009-04	46 (23.0)	50 (25.0)	50 (25.0)	54 (27.0)
DY	2009-05 to 2025-12	67 (33.5)	61 (30.5)	40 (20.0)	32 (16.0)
Reas.	1976-01 to 1992-08	59 (29.5)	51 (25.5)	47 (23.5)	43 (21.5)
Reas.	1992-09 to 2009-04	49 (24.5)	65 (32.5)	41 (20.5)	45 (22.5)
Reas.	2009-05 to 2025-12	60 (30.0)	58 (29.0)	32 (16.0)	50 (25.0)

The lag-1 transition matrices are reported in Tables 4a-c. Gardner-Knopoff and Deniz-Yucemen exhibited moderate changes in transition composition without persistent concentration along the diagonal. The Reasenber matrix showed stronger diagonal structure in the first and final periods. These features suggest that low- and high-activity states were more likely to persist under Reasenber declustering, but their statistical relevance must be evaluated with the entropy and permutation results.

Table 4
a. Lag-1 transition probabilities for the Gardner-Knopoff catalogue.

Period	Current	Next D1	Next D2	Next D3	Next D4
1976-01 to 1992-08	D1	0.422	0.205	0.205	0.169
	D2	0.333	0.091	0.364	0.212
	D3	0.413	0.152	0.217	0.217
	D4	0.514	0.135	0.189	0.162
1992-09 to 2009-04	D1	0.309	0.127	0.255	0.309
	D2	0.320	0.040	0.240	0.400
	D3	0.255	0.127	0.364	0.255
	D4	0.234	0.156	0.250	0.359
2009-05 to 2025-12	D1	0.423	0.179	0.244	0.154
	D2	0.432	0.227	0.159	0.182
	D3	0.310	0.286	0.190	0.214
	D4	0.371	0.229	0.257	0.143

Table 4
b. Lag-1 transition probabilities for the Deniz-Yucemen catalogue.

Period	Current	Next D1	Next D2	Next D3	Next D4
1976-01 to 1992-08	D1	0.283	0.383	0.200	0.133
	D2	0.345	0.164	0.291	0.200
	D3	0.256	0.279	0.233	0.233
	D4	0.341	0.244	0.122	0.293
1992-09 to 2009-04	D1	0.283	0.304	0.174	0.239
	D2	0.245	0.184	0.265	0.306
	D3	0.160	0.340	0.260	0.240
	D4	0.222	0.185	0.296	0.296
2009-05 to 2025-12	D1	0.403	0.254	0.239	0.104
	D2	0.246	0.377	0.230	0.148
	D3	0.308	0.282	0.103	0.308
	D4	0.406	0.312	0.156	0.125

Table 4
c. Lag-1 transition probabilities for the Reasenberg catalogue.

Period	Current	Next D1	Next D2	Next D3	Next D4
1976-01 to 1992-08	D1	0.328	0.362	0.190	0.121
	D2	0.373	0.196	0.275	0.157
	D3	0.277	0.340	0.170	0.213
	D4	0.186	0.070	0.326	0.419
1992-09 to 2009-04	D1	0.327	0.327	0.245	0.102
	D2	0.219	0.359	0.203	0.219
	D3	0.220	0.317	0.171	0.293
	D4	0.200	0.289	0.200	0.311
2009-05 to 2025-12	D1	0.517	0.333	0.050	0.100
	D2	0.281	0.298	0.175	0.246
	D3	0.188	0.281	0.281	0.250
	D4	0.140	0.220	0.200	0.440

Table 5 summarizes the information measures and permutation tests. Shannon entropy remained high in all catalogue-period combinations, indicating that the monthly sequences were not dominated by a single activity state. Conditional entropy was also high, but the reduction from Shannon entropy varied substantially among declustering methods. Gardner-Knopoff produced lag-1 mutual information of only 0.0171–0.0253 bits, corresponding to 0.89–1.34% explained uncertainty. All three values were below the permutation mean and were non-significant. Deniz-Yucemen retained somewhat more information but none of its periods reached statistical significance.

Reasenberg yielded a different pattern. Lag-1 mutual information was significant in the first period and the final period, explaining higher percentage of the next-month's uncertainty. Their bias-corrected values were positive. The middle period was indistinguishable from randomized ordering. The first and final Reasenberg results also remain significant under a conservative Bonferroni threshold of $0.05/9 = 0.0056$ for the nine catalogue-period tests.

Table 5

Entropy, lag-1 mutual information, and permutation-test results for the three declustered catalogues.

Cat.	Period	$H(S)$	$H(S_{t+1} S_t)$	$I(S_t; S_{t+1})$	PI (%)	p	Perm. MI	Bias-corr. MI
GK	1976-01 to 1992-08	1.8926	1.8636	0.0253	1.34	0.668	0.0340	-0.0087
GK	1992-09 to 2009-04	1.9274	1.9037	0.0241	1.25	0.694	0.0335	-0.0094
GK	2009-05 to 2025-12	1.9272	1.9070	0.0171	0.89	0.868	0.0335	-0.0164
DY	1976-01 to 1992-08	1.9802	1.9340	0.0467	2.36	0.186	0.0336	0.0131
DY	1992-09 to 2009-04	1.9977	1.9678	0.0292	1.46	0.550	0.0334	-0.0042
DY	2009-05 to 2025-12	1.9385	1.8860	0.0505	2.61	0.145	0.0336	0.0169
Reas.	1976-01 to 1992-08	1.9900	1.8850	0.1050	5.28	0.001	0.0332	0.0718
Reas.	1992-09 to 2009-04	1.9770	1.9435	0.0332	1.68	0.434	0.0332	-0.0000
Reas.	2009-05 to 2025-12	1.9620	1.8251	0.1378	7.02	< 0.001	0.0339	0.1038

The lagged mutual-information curves reinforce this distinction (Fig. 4). Gardner-Knopoff and Deniz-Yucemen do not exhibit a common or monotonic dependence pattern across lags. The isolated Gardner-Knopoff increase at lag 12 in the final period should therefore be treated as descriptive rather than as evidence of annual periodicity. Reasenber displays stronger short-range dependence, particularly at lags 1–2 in the final period. Estimates beyond lag 1 were not subjected to separate significance tests and are interpreted descriptively.

The 20-year moving-window results show consistently low lag-1 mutual information for Gardner-Knopoff and moderate but irregular values for Deniz-Yucemen (Fig. 5). Reasenber follows a U-shaped trajectory: mutual information decreases from the early windows to the late 1990s and then rises after the early 2000s, reaching approximately 0.095 bits in the final window. Because adjacent windows overlap substantially, these trajectories describe temporal evolution and are not independent significance tests.

The comparison with randomized state orderings provides the clearest separation among methods (Fig. 6). Gardner-Knopoff removes nearly all detectable month-to-month information, and Deniz-Yucemen retains modest but non-significant dependence. Standard Reasenber declustering retains statistically significant temporal organization in the early and recent periods. This finding does not establish operational earthquake predictability. Rather, it demonstrates that the information measured in monthly

activity is sensitive to how dependent events are identified and removed. The substantially larger Reasenbergs catalogue preserves more temporally concentrated activity, which can increase apparent short-term dependence.

Taken together, the results show that the temporal information detected in monthly earthquake activity is not independent of catalogue preparation. The Gardner–Knopoff and Deniz–Yüccemen methods produced broadly similar activity series and removed nearly all statistically detectable month-to-month dependence. In contrast, Reasenbergs retained substantially more events and significant temporal organization in the early and recent periods. These findings should not be interpreted as a definitive ranking of declustering algorithms. Rather, they demonstrate that algorithms based on different event-association rules can produce catalogues with markedly different information structures, even when the same original catalogue, completeness threshold, temporal resolution, and analytical procedure are used.

The findings should also be considered in the light of several limitations. The comparison was restricted to three deterministic declustering procedures representing a conventional global window method, a regionally adopted window method, and an interaction-based clustering algorithm; stochastic ETAS-based and nearest-neighbor approaches were not included. The results may also depend on the selected parameter values, the common completeness threshold, monthly aggregation, and the discretization of event counts into four catalogue-specific activity states. Moreover, the permutation tests assess temporal ordering separately within each catalogue and period.

5. Conclusions

This study compared the temporal information retained in 600 months of monthly earthquake activity after applying three alternative declustering procedures to the same homogenized Türkiye catalogue. The principal conclusions are as follows:

- Shannon entropy remained high across all catalogue-period combinations. Monthly activity was therefore distributed among several states rather than being dominated by one persistent level.
- Gardner-Knopoff produced the weakest month-to-month dependence. Lag-1 mutual information ranged from 0.0171 to 0.0253 bits, explained only 0.89–1.34% of next-month uncertainty, and was non-significant in all three periods.
- Deniz-Yuccemen retained slightly more temporal information, but none of its period-specific results differed significantly from randomized state ordering.
- Reasenbergs yielded significant lag-1 dependence in the first and final periods, corresponding to greater reductions in next-month uncertainty. Both results remained significant under the Bonferroni threshold, whereas the middle period was non-significant.
- The moving-window and multi-lag results confirmed that temporal organization was consistently weak under Gardner-Knopoff, modest and irregular under Deniz-Yuccemen, and substantially stronger under Reasenbergs, particularly in the recent portion of the catalogue.

Overall, the measured temporal information is not invariant to declustering. Magnitude-dependent window methods removed nearly all detectable month-to-month dependence, whereas standard Reasenbergs declustering preserved significant organization during the early and recent periods. This contrast is the central result of the study: conclusions regarding seismic predictability can depend materially on how dependent events are identified and removed. The retained dependence in the Reasenbergs catalogue may reflect temporally concentrated activity that remains after declustering and should not be interpreted as deterministic or operational earthquake predictability.

Declarations

Conflict of Interest

The author declares that there are no financial or non-financial conflicts of interest related to this study.

Funding

The author received no specific funding for this research.

Author Contributions

Hakan Karaca: Conceptualization, methodology, software, formal analysis, investigation, data curation, visualization, validation, writing—original draft, and writing—review and editing. The author read and approved the final manuscript.

Acknowledgements

The author gratefully acknowledges the Kandilli Observatory and Earthquake Research Institute (KOERI) for providing access to the earthquake catalogue used in this study.

Data Availability Statement

The earthquake catalogue used in this study is publicly available from the Kandilli Observatory and Earthquake Research Institute earthquake database at <http://www.koeri.boun.edu.tr/sismo/zeqdb/>. The processed catalogues, derived monthly activity series, and MATLAB codes supporting the findings of this study are available from the corresponding author upon reasonable request.

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Figures

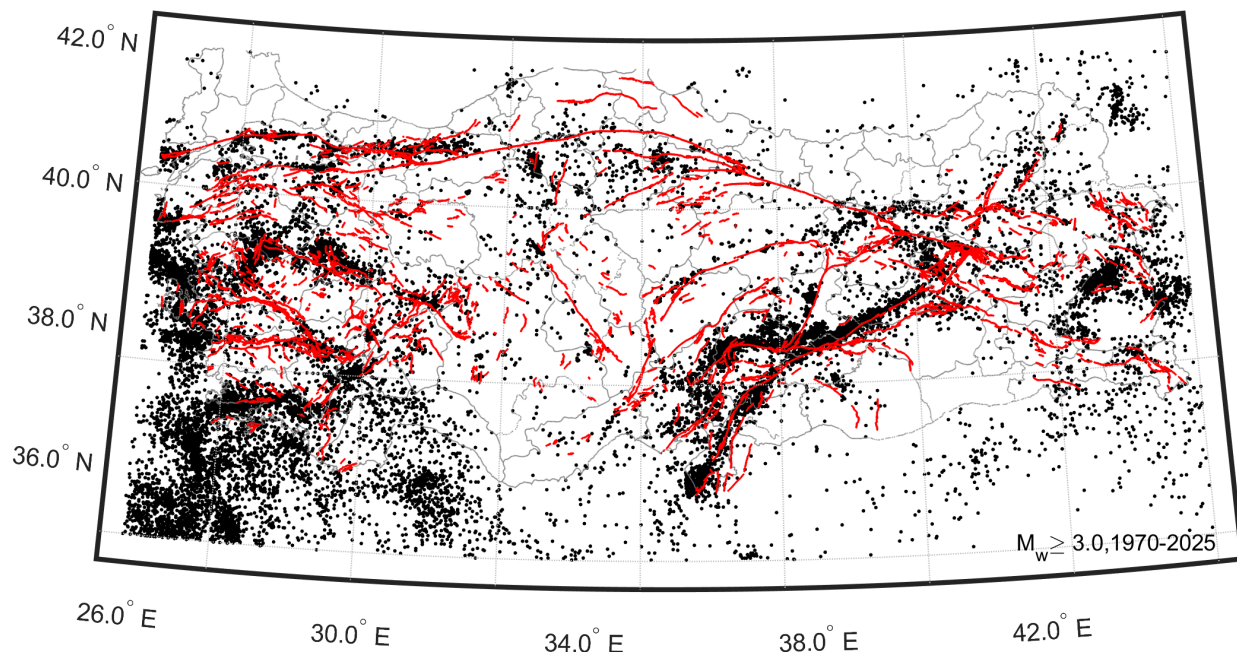


Figure 1

The Study Area Covers Entire Türkiye, 26° – 45° E and 35° – 42° N, Data is obtained from KOERI, 2026

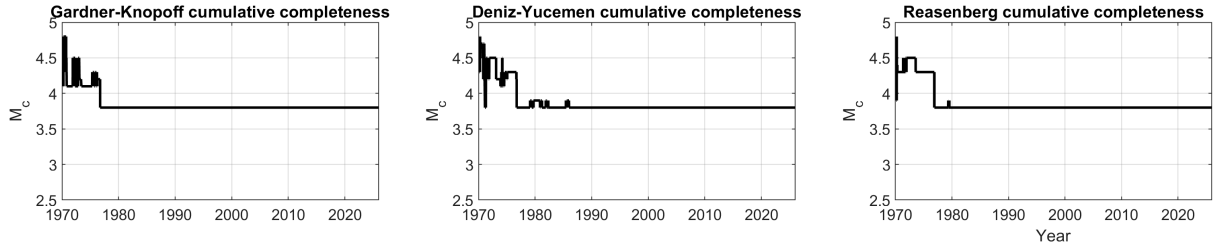


Figure 2

Temporal Evolution of the Cumulative Magnitude of Completeness (M_c) Estimated Using The Maximum-Curvature Method for The Catalogues Declustered by The Gardner–Knopoff, Deniz–Yüçemen, And Reasenber Methods.

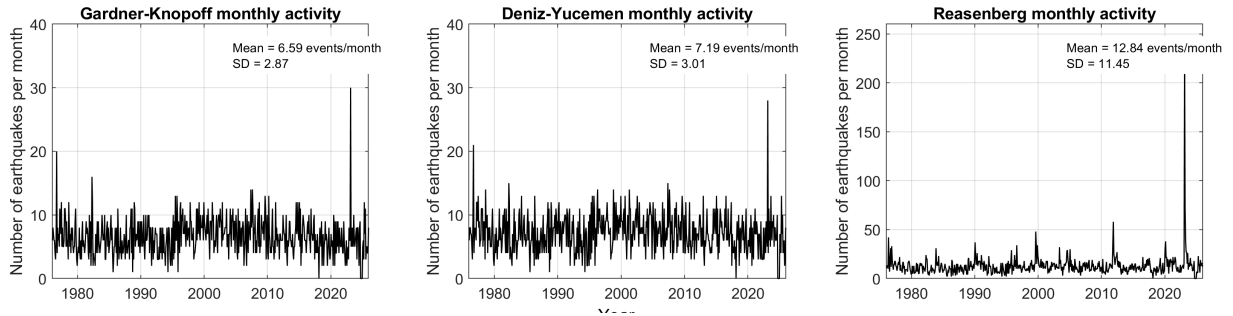


Figure 3

Monthly earthquake counts obtained from the catalogues declustered using the Gardner–Knopoff, Deniz–Yüçemen, and Reasenber methods for $M_{w \geq 3.9}$ during 1976–2025.

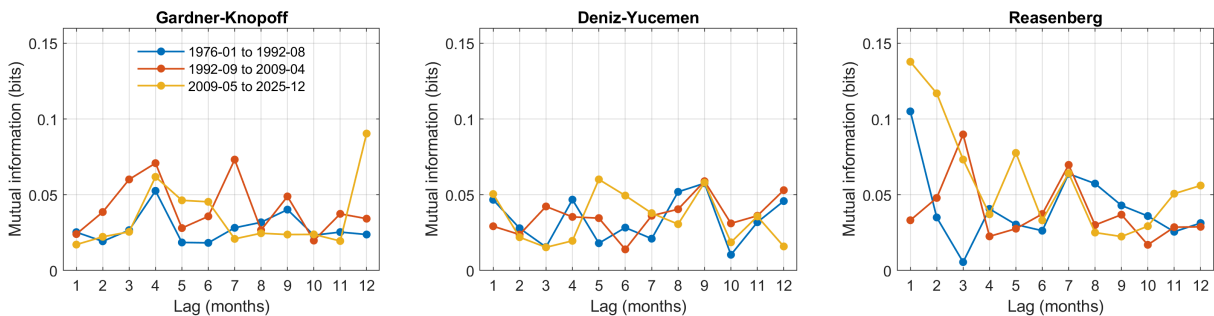


Figure 4

Lagged mutual information at 1-12 months for the three independent periods and declustering methods.

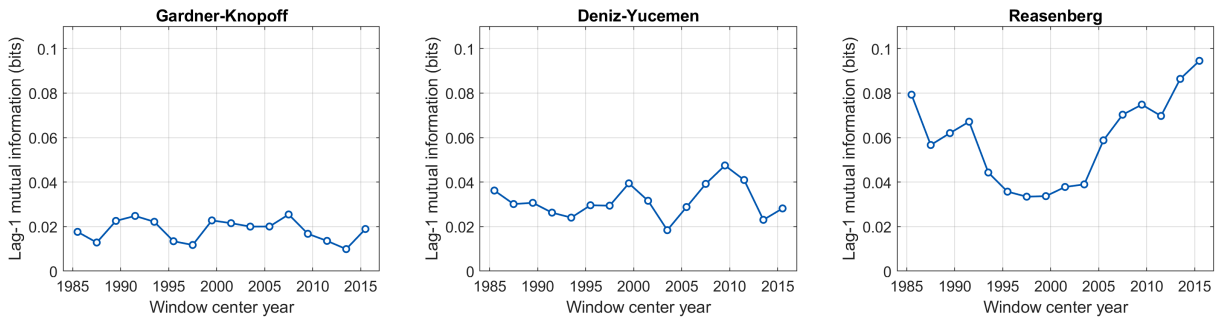


Figure 5

Lag-1 mutual information in 20-year moving windows advanced in two-year steps. Adjacent windows overlap and are interpreted descriptively.

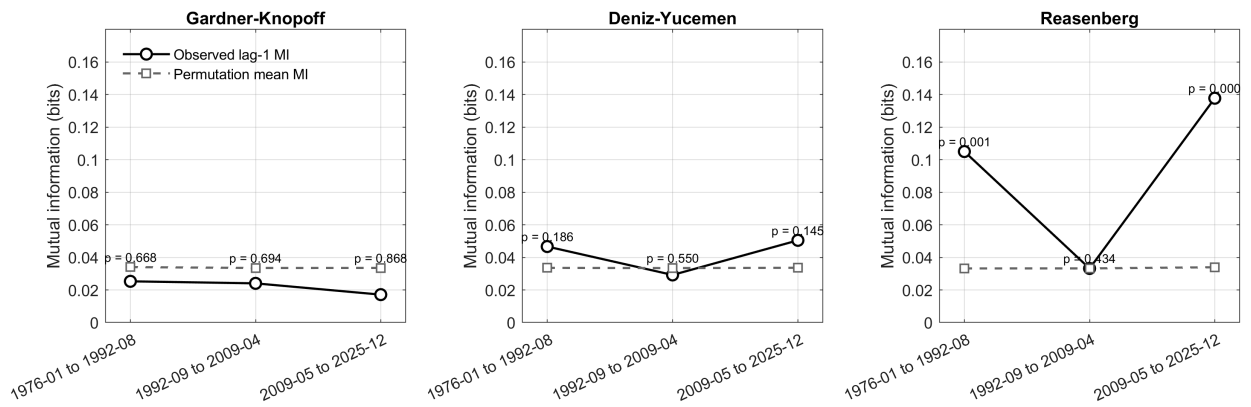


Figure 6

Observed lag-1 mutual information and permutation-based means for the three declustering methods. P values are based on 5,000 within-period permutations.