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Doctorate Thesis in Geophysics

**Parametrization of seismic sources and quantification of  
uncertainties in probabilistic seismic and tsunami  
forecasts**

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# ABSTRACT

Earthquakes represent one of the most complex and unpredictable natural hazards, and their statistical characterization is essential for seismic hazard and risk assessment. Despite decades of research, the mechanisms controlling the size distribution of earthquakes and the identification of possible precursory patterns remain debated. This uncertainty stems both from physical complexity and from methodological limitations, such as catalog incompleteness and biases in magnitude estimation.

This thesis addresses these limitations from different perspectives. First, it investigates the role of catalog completeness and magnitude correlations in shaping statistical inferences on earthquake occurrence. Using synthetic and real earthquake catalogs, I show that apparent magnitude correlations and anomalously low  $b$ -values are often artifacts of short-term incompleteness rather than evidence of precursory processes.

Second, the thesis explores how physical and structural factors of the lithosphere control earthquake size distributions. I show that variations in the  $b$ -value correlate not only with regional heat flow and tectonic regime, but also with fault geometry and kinematics. These findings indicate that earthquake statistics are not universal but strongly conditioned by both geodynamic environment and local fault architecture.

Third, I develop a Bayesian framework for focal mechanism forecasts that explicitly accounts for magnitude dependence. Accurate forecasts of focal mechanisms are fundamental not only for seismic hazard assessment but also for tsunami hazard modeling, which requires rapid knowledge of fault geometry and kinematics immediately after an earthquake. The results show that ignoring magnitude dependence introduces systematic biases in hazard models, whereas it produces more reliable and physically consistent forecasts with direct implications for both seismic and tsunami risk assessment. This approach provides a foundation for incorporating physical constraints into operational forecasting in near-real-time scenarios.

Finally, the thesis examines the identification of foreshocks. A comparison between Nearest Neighbor (NN) and ETAS-based declustering reveals that the widely used NN method, although popular, fails to capture the full range of foreshock properties defined by ETAS. This finding suggests that the identification of foreshocks is sensitive to the chosen methodology and that caution is required when interpreting them as genuine physical precursors.

In summary, this thesis extends our understanding of how both methodological choices and physical processes shape earthquake statistics. By emphasizing the importance of unbiased magnitudes, consistent catalogs, and physically informed models, it contributes to more reliable earthquake forecasting and hazard assessment. Taken together, the results indicate that progress toward answering the central question—whether earthquakes are governed purely by

chance or by systematic physical rules—requires integrating high-quality data, robust statistical frameworks, and geodynamic context.

# SOMMARIO

I terremoti rappresentano uno dei pericoli naturali più complessi e imprevedibili, e la loro caratterizzazione statistica è fondamentale per la valutazione della pericolosità e del rischio sismico. Nonostante decenni di ricerca, i meccanismi che controllano la distribuzione delle magnitudo e l'identificazione di possibili *pattern* precursori rimangono oggetto di dibattito. Questa incertezza deriva sia dalla complessità fisica sia da limitazioni metodologiche, come l'incompletezza dei cataloghi e i *bias* nella stima delle magnitudo.

Questa tesi affronta tali limitazioni da diverse prospettive. Innanzitutto, indaga il ruolo dell'incompletezza dei cataloghi e delle correlazioni tra magnitudo nel determinare le inferenze statistiche sulla sismicità. Utilizzando cataloghi sismici sintetici e reali, mostro che le apparenti correlazioni tra magnitudo e i valori anomali e bassi del *b-value* sono spesso artefatti dovuti a incompletezza a breve termine, piuttosto che evidenza di processi precursori.

In secondo luogo, la tesi esplora come i fattori fisici e strutturali della litosfera influenzino la distribuzione delle magnitudo dei terremoti. In particolare, mostro che le variazioni del *b-value* sono correlate non solo con il flusso termico regionale e il regime tettonico, ma anche con la geometria e la cinematica delle faglie. Questi risultati indicano che le statistiche dei terremoti non sono

universali, ma fortemente condizionate sia dall'ambiente geodinamico sia dall'architettura locale delle faglie.

In terzo luogo, sviluppo un quadro bayesiano per il *forecast* dei meccanismi focali che tenga esplicitamente conto della dipendenza dalla magnitudo. *Forecast* accurati dei meccanismi focali sono fondamentali non solo per la valutazione della pericolosità sismica, ma anche per la modellazione del rischio tsunami, che richiede una conoscenza rapida della geometria e della cinematica delle faglie immediatamente dopo un terremoto. I risultati mostrano che ignorare la dipendenza dalla magnitudo introduce *bias* sistematici nei modelli di pericolosità, mentre includerla produce *forecast* più affidabili e coerenti dal punto di vista fisico, con implicazioni dirette sia per la valutazione del rischio sismico sia per quello tsunami. Questo approccio fornisce una base per integrare vincoli fisici nelle previsioni operative in scenari quasi in tempo reale.

Infine, la tesi esamina l'identificazione dei *foreshock*. Un confronto tra il metodo *Nearest Neighbor* (NN) e il *declustering* basato su ETAS rivela che l'approccio NN, sebbene ampiamente utilizzato, non riesce a catturare l'intero spettro delle proprietà dei *foreshock* definite da ETAS. Questo risultato suggerisce che l'identificazione dei *foreshock* è sensibile alla metodologia scelta e che è necessaria cautela nell'interpretarli come veri precursori fisici.

In sintesi, questa tesi amplia la nostra comprensione di come le scelte metodologiche e i processi fisici plasmino le statistiche dei terremoti. Sottolineando l'importanza di magnitudo omogenee, cataloghi consistenti e

modelli fisicamente basati, contribuisce a *forecast* sismici più affidabili. Complessivamente, i risultati indicano che per fare progressi nel rispondere alla domanda centrale—se i terremoti siano governati esclusivamente dal caso o da regole fisiche sistematiche—è necessario integrare dati di alta qualità, quadri statistici robusti e contesto geodinamico.



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## Part 1

# INTRODUCTION



## INTRODUCTION

God does not play dice.<sup>1</sup>

Or does He?

Since ancient times, philosophers and intellectuals have reflected on the role of randomness in the world. What is chance? Is there a hidden strict order behind what seems unpredictable, or is reality governed by completely random events?

In everyday life, and even more so in modern society, many catastrophic natural phenomena are commonly perceived as random or inevitable events: earthquakes, floods, landslides seem to happen “by chance,” without any apparent reason. This perception often fuels fear and a sense of helplessness. However, what appears random is not necessarily incomprehensible: natural disasters always have a physical basis and follow observable, though complex, dynamics.

---

<sup>1</sup> Einstein wrote this in a letter to Max Born in December 1926, expressing his skepticism about the probabilistic interpretation of quantum mechanics.

Among these phenomena, earthquakes provide the clearest example of this apparent randomness. They seem to occur exactly when no one expects them, striking without warning and generating panic. But does this perception of total unpredictability really reflect reality? Looking back and analyzing major seismic events, recognizable characteristics often emerge: stress accumulation along faults, sequences of smaller events, specific spatial or temporal patterns. These are not deterministic signals in the strict sense, but they show potential physical laws and underlying processes regulating seismicity.

When these known features are incorporated into forecasting models—together with the acknowledgment that they are insufficient for precise prediction, the results show that the use of probabilistic forecasting cannot be equated to simply tossing a dice. These models do not make exact predictions of the “when” and “how” of the next earthquake but rather aim to quantify the probability of event occurrence based on available information and physical laws. Uncertainty therefore does not mean complete ignorance but reflects the complexity of natural processes and the need for statistical and physical tools to interpret and reduce it.

Beyond improving seismic risk management, deepening knowledge of earthquake generation mechanisms is also crucial for forecasting other subsequent natural phenomena such as landslides, liquefaction, or tsunamis. Although tsunami genesis is relatively well understood - they primarily arise from the sudden displacement of large water volumes - the prediction of

seismically generated tsunamis depends on the characteristics of the triggering earthquake, such as magnitude and fault geometry.

Scientific research therefore allows us to reduce uncertainty and transform what seems random into useful knowledge. Nevertheless, the natural world always retains a degree of unpredictability. The idea that 'God does not play dice' might tempt us to believe that everything follows strict and deterministic laws. However, experience with complex phenomena such as earthquakes teaches us that it may be more realistic to admit that it will never be possible to know everything with absolute certainty. Forecasting science does not seek to eliminate uncertainty but to quantify it, manage it, and use available information to make more informed decisions.

This work aims to provide insights that can contribute to more reliable forecasts by investigating the statistical properties of earthquakes, exploring variations in magnitude distributions and testing different physical and statistical models of earthquake occurrence.

### 1.1 Natural hazard forecasting

A prediction is a deterministic statement (usually, YES or NO) asserting that a hazardous event will or will not occur in a specific space-time-magnitude window. They become scientifically and practically relevant when spatial and temporal windows are small and magnitude/intensity thresholds are meaningful for risk management.

A forecast, on the other hand, is a probabilistic statement that specifies the probability of an event occurring in each spatio-temporal-magnitude subdomain. The probability ranges from 0 (no chance) to 1 (certainty).

Historically, scientists favored deterministic predictions, partly because they were trained in a deterministic mindset and partly because such predictions directly support alarm systems. However, issuing alarms also involves economic and political decisions, which are beyond the scientist's role. Deterministic predictions can thus blur the distinction between scientific analysis and decision-making responsibility.

A more robust approach relies on probabilistic forecasts. For example, alarms can be set whenever the probability of exceedance exceeds a chosen threshold. Probabilistic forecasts provide a richer description of potential future scenarios, offering a better foundation for risk-informed decision-making, particularly when the event probability is low or uncertainty is high (Vere-Jones 1995).

### 1.1.1 Earthquake forecasting

A probabilistic earthquake forecast quantifies the probability of future events within a given space–time–magnitude window. Formally, a forecast is represented as a statistical distribution over the random variable of interest—typically the number, location, and magnitude of earthquakes—allowing explicit evaluation of uncertainties and the probability of specific outcomes.

One of the most striking aspects of seismicity is its clustering in time and space: earthquakes tend to trigger other earthquakes. Its temporal behavior is formalized by the modified Omori law (Utsu 1957):

$$X(t) = \frac{K}{(t + c)^p}, \quad (1.1)$$

where  $X(t)$  is the number of earthquakes per unit time at time  $t$  after a mainshock,  $K$  is the sequence productivity, and  $c$  and  $p$  regulate the temporal decay. Similarly, aftershock spatial distribution follows a power-law decay with distance from the mainshock (Felzer and Brodsky 2006).

Clustering also depends on the magnitude of the initiating earthquake: larger events generally produce richer sequences, although local variability can be significant (De Arcangelis, *et al.* 2016).

Earthquake magnitudes typically follow the Gutenberg-Richter (GR) law:

$$\log_{10} N(M) = a - b(M - M_{min}) \quad (1.2)$$

where  $N(M)$  is the number of earthquakes with magnitude  $\geq M$ ,  $b$  is the so-called  $b$ -value, and  $M_{min}$  is the minimum magnitude considered.

Based on those empirical observations, earthquake forecasting models can be classified into two conceptual types: cascade models and pre-slip models.

Cascade models treat all earthquakes as potentially capable of triggering subsequent events, regardless of their size. In this view, seismicity evolves as a branching process, where smaller earthquakes can occasionally generate larger

ones, and the overall sequence emerges from the cumulative interaction of many events.

In contrast, pre-slip models focus on the physical processes leading up to a large earthquake.

While cascade models excel at capturing statistical patterns of clustering and aftershock sequences, pre-slip models aim to identify specific signals that could indicate an imminent large earthquake. This physically grounded perspective offers a possible explanation for the small events that occur in the hours or days preceding a major event.

### 1.1.2 Probabilistic forecasting models: the ETAS model

The main representatives of the cascade models are the Reasenberg and Jones (RJ, 1989) and the Epidemic-Type Aftershock Sequence (ETAS, Ogata 1988) models.

The RJ model integrates the Omori's law (eq. 1.1) and the GR distribution (eq. 1.2) into a probabilistic framework for aftershocks, defining the instantaneous rate as:

$$\lambda(t) = \frac{K 10^{b(M-M_{min})}}{(t+c)^p}, \quad (1.3)$$

with the number of aftershocks  $N(T)$  treated as a Poisson random variable with parameter  $\int_0^T \lambda(t) dt$ . This formulation allows estimating the probability of at least one event of magnitude  $M$  in a future time window.

The ETAS model extends this concept by allowing every earthquake to trigger other earthquakes, without a priori distinction between foreshocks, mainshocks, or aftershocks. Unlike RJ, which only considers the temporal evolution and magnitude distribution of aftershocks, ETAS explicitly introduces a spatial component, making it a full space–time–magnitude model. Its general formulation is:

$$\lambda(t, \vec{x}|H) = \mu(\vec{x}) + \sum_{i:t_i < t} K(M_i)g(t - t_i)f(\vec{x} - \vec{x}_i), \quad (1.4)$$

where  $\mu(\vec{x})$  is the background rate,  $g(t - t_i)$  is the temporal decay,  $f(\vec{x} - \vec{x}_i)$  is the spatial decay, and  $K(M_i)$  is the magnitude-dependent productivity. The magnitude of new events is usually assumed independent of previous events and distributed according to the GR law (eq. 1.2):

$$\lambda(t, \vec{x}, M|H) = \lambda(t, \vec{x}|H)p(M). \quad (1.5)$$

This assumption of magnitude independence represents the main limitation to forecasting large earthquakes: since the magnitudes are sampled from an exponential law (the GR law, eq. 1.2), the probability of extreme events in the right tail is always small.

Forecasts are produced by simulating synthetic catalogs, where background events generate other events according to the distributions of time, space, and magnitude, iteratively producing sequences consistent with the observed seismic history (Zhuang and Touati 2015).

### 1.1.3 $b$ -values

The  $b$ -value is a key parameter in the GR law (eq. 1.2), describing the relative occurrence of small and large earthquakes within a region. Some researchers interpreted this parameter as a proxy for the stress state in the crust, with lower  $b$ -values indicating higher stress levels and vice versa (Amitrano 2003; Goebel, *et al.* 2013; Gulia, *et al.* 2018; 2020; Gulia and Wiemer 2010; Schorlemmer, *et al.* 2005; Tormann, *et al.* 2015; Scholz 2015). Consequently, some observations of temporal changes in the GR  $b$ -value (eq. 1.2) before large earthquakes have suggested that such variations may reflect evolving stress conditions in the crust. These changes are often interpreted as a proxy for the approach to failure, thereby offering a potential forecasting tool. While cascade models, such as ETAS, interpret all earthquakes as statistically similar events capable of triggering further ones, pre-slip models explicitly link precursory phenomena to the nucleation of a main rupture. In this framework,  $b$ -value variations are incorporated as indicators of progressive weakening and slip acceleration on a fault patch, representing a departure from the purely statistical cascade view toward physics-based pre-slip models (e.g. Gulia and Wiemer 2019).

It is important to emphasize that interpreting the  $b$ -value is not always straightforward (Marzocchi, *et al.* 2020). While the  $b$ -value is often considered a direct proxy for the stress state in the crust or for other physical conditions such as faulting style, creeping or locked patches, rock heterogeneity, fluid

pressure, or critical nucleation length (Scholz 1968; Main, *et al.* 1989), recent studies highlight that its estimation and interpretation strongly depend on the spatial and temporal scale of the analysis, as well as on the expert choices made during data processing (Herrmann and Marzocchi 2021). Factors such as catalog completeness, magnitude range, sample size, magnitude binning, and the chosen magnitude scale can bias the estimation of the  $b$ -value, making it sensitive to subjective methodological decisions (Kagan 1999; 2002; 2003; Marzocchi, *et al.*, 2020; Herrmann and Marzocchi 2021).

Complex earthquake sequences further complicate the picture: distinct seismogenic zones may exhibit different magnitude–frequency distributions (MFDs), so that averaging over the whole region or smoothing over space or time can mask meaningful variations (Herrmann, *et al.* 2022).

Therefore, a physically meaningful interpretation of  $b$ -value variations requires isolating seismogenic zones and considering their spatiotemporal evolution. This approach can be complemented by the standard MLE estimate of the  $b$ -value (Aki 1965; Marzocchi and Sandri 2003):

$$\hat{\beta} = \hat{b} \ln 10 = \frac{1}{\langle M \rangle - M_{min}}, \quad (1.6)$$

and its corrected form for small samples:

$$\hat{\beta}_{corr} = \hat{\beta} \frac{N-1}{N}, \quad (1.7)$$

whose uncertainty is given by the standard error:

$$\sigma = \frac{\hat{\beta}}{\sqrt{N}} \quad (1.8)$$

It should always be accompanied by an evaluation of exponentiality (Herrmann and Marzocchi 2020) and sensitivity to choices such as the magnitude of completeness  $M_C$ . In other words, the  $b$ -value alone provides only a partial view of seismicity, and a careful spatiotemporal analysis of the MFD is essential to avoid ambiguous or misleading conclusions about  $b$ -values variations.

### 1.1.4 Foreshocks

In the most classical definition, foreshocks are smaller earthquakes that occur before a so-called mainshock, i.e., the largest earthquake of a sequence. The distinction between foreshocks, mainshocks and aftershocks can be made only *a posteriori*, hence it is completely irrelevant for real-time earthquake forecasting. In a more loose definition commonly adopted, foreshocks are the smaller earthquakes that anticipate large earthquakes, independently whether they are mainshocks or not. Their potential for earthquake forecasting has been debated for decades and two main interpretations exist: in the first, foreshocks are considered passive tracers of a preparatory tectonic process, such as slow aseismic slip on the hosting fault, which may indicate the imminent occurrence of a mainshock (Das and Scholz 1981; Kanamori 1981; Mignan 2014); second, foreshocks are part of the normal behavior of seismicity: they are simply smaller

earthquakes that can occasionally trigger a larger event, without providing reliable predictive information (Ogata 1988; Reasenberg and Jones 1989; Helmstetter and Sornette 2003).

In the ETAS models, earthquakes can be part of the background (independent from previous events) or triggered by previous earthquakes, and their magnitude is assumed to be independent from the past history, therefore, in this "ETAS world" the distinction between foreshocks, mainshocks and aftershocks makes no sense. Since ETAS models are currently the best forecasting models, they may be used as reference to check departures between real earthquakes and synthetic catalogs generated by ETAS. Although ETAS models provide a reliable statistical description of earthquake sequences and short-term forecasting (Page and van Der Elst 2022; Nanjo, *et al.* 2012), some discrepancies in foreshock sequences have been advocated (Manganiello, *et al.* 2023). These deviations, if real, may suggest that additional processes, not captured by classical ETAS models, may influence seismicity. In general, empirical studies show that the identification of anomalous foreshocks strongly depends on the magnitude range considered. When micro-seismicity is included, foreshocks may reveal preparatory processes (Jones, *et al.* 1982). In contrast, analyses restricted to larger magnitudes generally support cascade-type triggering models such as ETAS (Ogata 1988; Reasenberg and Jones 1989; Helmstetter and Sornette 2003; Felzer, *et al.* 2004). Because of this still large

uncertainty, foreshocks are still never used in practice to forecast large earthquakes.

However, the main challenge remains their real-time identification: foreshocks are only recognized as such a posteriori, once a larger mainshock has occurred. This intrinsic ambiguity strongly limits their predictive value, since, in real time, it is generally impossible to distinguish whether a small event is the first sign of a foreshock sequence or simply part of the ongoing seismicity producing a sequence without any relevant event.

Several approaches have been proposed to overcome this issue by recognizing specific physical characteristics of foreshocks (Gulia and Wiemer 2019; Zaccagnino, *et al.* 2024; Lippiello, *et al.* 2025), but since such features cannot always be measured consistently across different regions, the most robust and objective strategies rely on machine-learning-based clustering methods (Wetzler, *et al.* 2023; Zaliapin and Ben-Zion 2013; Baiesi and Paczuski 2004; Frohlich and Davis 1990).

### 1.2 Tsunami forecasting

Tsunami forecasting relies on a probabilistic framework conceptually similar to the one adopted for earthquakes. The tsunamis of seismic origin are more frequent and larger than the ones from other sources, and thus many efforts have been dedicated to assessing the so-called Seismic Probabilistic Tsunami Hazard Assessment (SPTHA) (Geist and Parsons 2006; Selva, *et al.* 2016). SPTHA usually decomposes the problem into four main steps. First, a set of possible

tsunami sources is generated hierarchically exploring the aleatory variability of source parameters. Since the source characterization (geometry and size) directly controls seafloor displacement and tsunami initiation, it becomes crucial to work on improving forecasts of the specific characteristics of the seismic source beyond the typical characterization required for seismic analyses, by providing information not only on earthquake location and magnitude, but also on fault size and source geometry (focal mechanism). Second, the offshore tsunami propagation is simulated, often using pre-computed databases of elementary scenarios that can be linearly combined to approximate the wave field for any given source at many offshore target points. Third, the coastal amplification and inundation are estimated, either through simplified laws such as Green's law for regional-scale assessments, or through high-resolution numerical simulations for site-specific studies. Finally, these components are integrated to obtain hazard curves, which quantify the annual probability of exceeding a given tsunami intensity measure at a target location.

### 1.3 Thesis outline

This thesis consists of six main chapters, discussed and written in collaboration with my supervisors and colleagues. Two of them have already been published, one has been submitted and under review, and the other three are in preparation for submission.

The central theme of this thesis is the critical assessment of what controls earthquake occurrence and characteristics, distinguishing true physical signals

from statistical or methodological artifacts, in order to improve the capability to produce unbiased forecasts about future seismicity and its main characteristics.

In Chapter 2, I investigate the assumption of magnitude independence in earthquake forecasting by testing correlations between the magnitudes of successive earthquakes. I focus first on the 2019 Ridgecrest foreshock sequence, where I find significant magnitude correlation and an anomalously low  $b$ -value, which I show to be the result of short-term incompleteness (STI) rather than precursory processes. Using synthetic simulations and extending the analysis to seismicity in southern California, I demonstrate that magnitude correlation is a pervasive artifact of STI, making it a more reliable indicator of catalog incompleteness than a proxy for the occurrence of higher magnitudes. These results have been published in:

Corrado, P., Herrmann, M., and Marzocchi, W. (2025). Earthquake Magnitude Correlations Expose Short-Term Catalog Incompleteness. Seismological Research Letters, 96(2A), 909-919. <https://doi.org/10.1785/0220240277>

In Chapter 3, we examine the reported temporal variations of the  $b$ -value during the 2016/17 central Italy earthquake sequence, particularly the anomalous behavior before the  $M_w 6.5$  Norcia mainshock, which has been suggested to be a precursor of the largest earthquake of the sequence. Using machine learning techniques, we show that this anomaly arises from the activation of two distinct seismicity volumes, characterized by asynchronous activity, different fault orientations, and persistently different  $b$ -values. When these structures are

analyzed separately, their  $b$ -values remain stable over time; only when combined does the apparent pre-mainshock increase emerge. This demonstrates that local temporal changes in the  $b$ -value largely reflect the shifting spatial distribution of seismicity across heterogeneous fault structures, rather than genuine temporal stress variations. These results have been published in:

Piegari, E., Corrado, P., Herrmann, M., and Marzocchi, W. (2025). Structural heterogeneities and spatial variations of seismicity drive temporal  $b$ -value changes. *Geophysical Research Letters*, 52(17), e2025GL116118.  
<https://doi.org/10.1029/2025GL116118>

In Chapters 4 and 5, I investigate the global-scale variability of earthquake magnitude–frequency distributions (MFDs), focusing on how both thermal conditions, tectonic environments, and faulting styles influence the  $b$ -value and the corner magnitude. These chapters highlight that earthquake size distributions are controlled by a combination of large-scale geodynamic environments, local fault kinematics, and thermal regimes, which jointly determine the likelihood of large earthquakes in different regions. These results have been recently submitted for publication.

Building on these results, in Chapter 6, I incorporate this knowledge into earthquake focal mechanism forecasting. By demonstrating that fault kinematics vary with magnitude and are not uniformly distributed across tectonic settings, I develop a magnitude-dependent approach that improves the physical and tectonic consistency of forecasts. Since focal mechanisms determine the tsunamigenic potential of earthquakes, this framework also

contributes to enhancing tsunami hazard assessment and tsunami warning, offering more reliable input for models that depend on realistic earthquake source characterizations. This chapter is an advanced draft of a manuscript that is planned for a soon submission.

In Chapter 7, I focus on foreshocks and the challenges in their identification. I compare Nearest Neighbor (NN) and ETAS declustering methods using synthetic catalogs with known parent–child relationships, quantifying how methodological choices affect foreshock statistics. This analysis highlights that foreshock patterns are strongly method-dependent and underscores the need for careful interpretation when linking observed sequences to potential physical precursors. Also, this chapter is an advanced draft of a manuscript that is planned for a soon submission.



Part 2

SCIENTIFIC  
CONTRIBUTIONS



## 2

# EARTHQUAKE MAGNITUDE CORRELATIONS EXPOSE SHORT-TERM CATALOG INCOMPLETENESS

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I contributed to the conceptualization, methodology, and investigation of the  
study, performed visualizations, wrote the original draft, and participated in the  
review and editing of the manuscript.

## 2.1 Abstract

The independence of earthquake magnitudes is a fundamental assumption and limitation in earthquake forecasting. To assess its validity, I examine correlations between the magnitude of successive earthquakes. I first investigate the 2019 Ridgecrest foreshock sequence and find significant magnitude correlation as well as an unusually low Gutenberg–Richter  $b$ -value ( $\approx 0.7$  using moment magnitudes). I demonstrate that these anomalous features are not indicative of a precursory phase, but a consequence of short-term incompleteness (STI) that is not detected by conventional methods to estimate catalog completeness. Synthetic simulations of this sequence support this explanation: imposing STI leads to significant magnitude correlation and biased  $b$ -value estimates. Expanding my investigation to seismicity across southern California reveals pervasive magnitude correlation due to STI, not limited to sequences with large earthquakes. My findings suggest that magnitude correlation is the most effective indicator of STI, rather than a characteristic of the underlying earthquake-generating process.

## 2.2 Introduction

The major limitation to the predictability of large earthquakes is the so-called magnitude-independence assumption: the magnitude of an earthquake is considered independent from the past and is randomly sampled from an exponential-like Gutenberg–Richter relation. This assumption is supported by empirical observations (Stallone and Marzocchi 2019) and the best performing earthquake forecasting models are based on it (Nanjo, *et al.* 2012; Taroni, *et al.* 2018). Yet, various studies on magnitude correlation, which is sometimes called “magnitude clustering”, find contrasting evidence (Lippiello, *et al.* 2008; 2012; Spassiani and Sebastiani 2016; Nandan, *et al.* 2022; Kwiatek, *et al.* 2023; Xiong, *et al.* 2023). For instance, while Lippiello *et al.* (2008) find that the next earthquake tends to have a similar magnitude than the previous one, Spassiani and Sebastiani (2016) found that a larger earthquake increases the probability for observing larger triggered earthquake, and Nandan *et al.* (2022) found that “earthquakes [...] are preferably triggered by events with a similar magnitude”, that is, “large events preferentially trigger other large earthquakes”. Besides potentially improving the forecasting of large earthquakes, it is suggested that magnitude correlation has physical implications that indicate precursory phenomena (Kwiatek, *et al.*, 2023; Xiong, *et al.*, 2023).

In principle, magnitude correlation could represent the connection between microscopic and macroscopic observations. For instance, successful lab-quake

predictions are mostly based on pre-slip observations (Leeman, *et al.* 2016; Bolton, *et al.* 2020; 2021), which, in the real Earth, could be mimicked by a series of earthquakes with similar (and therefore correlated) magnitudes (Ellsworth and Beroza 1995).

Nonetheless, numerous studies (Corral 2006; Davidsen and Green 2011; Petrillo and Zhuang 2022; 2023; Taroni 2018) support the magnitude-independence assumption by suggesting that magnitude correlation is solely due to short-term incompleteness (STI) in earthquake catalogs, that is, arising from undetectable smaller earthquakes that are triggered by a larger one (Kagan 2004; Helmstetter 2006; Hainzl 2016).

In this chapter, I aim at providing new insights on the existence and physical interpretation of magnitude correlation, examining whether it could be purely driven by STI. To this purpose, I start by analyzing the foreshocks of the first large earthquake of the 2019 Ridgecrest sequence ( $M_W 6.4$ ), which was already considered in prior statistical investigations (Nanjo 2020; Lee, *et al.* 2020; van der Elst 2021). This foreshock sequence intensified 30 minutes before the  $M_W 6.4$  event, including a  $M_W 4.0$ . The interest in this foreshock sequence derives from its unique characteristics: it features an extremely low  $b$ -value and a strong magnitude correlation (see Figure 2.1a-b). Specifically, the  $b$ -value is about 0.5 using local magnitudes (using a completeness magnitude calculated with conventional methods) for both a regional catalog (Hauksson, *et al.* 2012) and four sequence-specific high-resolution catalogs (Lee, *et al.* 2020; Shelly 2020;

Ross, *et al.* 2019; Liu, *et al.* 2020); the strong magnitude correlation is statistically significant for the two catalogs with the largest number of foreshocks (Lee, *et al.*, 2020; Ross, *et al.*, 2019). These results might suggest the existence of a preparatory phase of a large shock. Since this foreshock sequence is dominated by a  $M_W 4.0$  event, which triggered smaller earthquakes, I examine whether this first-order observation and interpretation holds in a more thorough analysis involving a method that estimates a reliable  $b$ -value in the presence of STI (van der Elst 2021) and a comparison with synthetic earthquake sequences that have a  $b$ -value of 1.0, independent magnitudes, and applied STI. Then, for a more general view on the relation between STI and magnitude correlation, I extend my analysis to all aftershock sequences in the southern California catalog of the last  $\sim 41$  years that have mainshock magnitudes  $m_M \geq 3.5$ . For those and their synthetic counterparts, I investigate the significance of magnitude correlations as a function of mainshock magnitude and minimum magnitude threshold.

## 2.3 Data and Methods

### 2.3.1 Analyzing the 2019 Ridgecrest sequence and comparison with synthetic earthquake sequences

#### 2.3.1.1 Data selection

I use the high-resolution catalog of Lee *et al.* (2020), which is based on template matching detection and relative relocation. For comparability with other catalogs (Hauksson, *et al.* 2012; Shelly, *et al.* 2020; Ross, *et al.* 2019;

Liu, *et al.* 2020) as shown in Figure 9.1, I only use events that occurred between 4 July 2019 00:00 UTC and the  $M_w 6.4$  (4 July 17:33:49 UTC), and within a radius of 37 km around the midpoint between the epicenters of the  $M_w 6.4$  and  $M_w 7.1$ . This selection was made to obtain a spatial selection of events that is common to both the Ross *et al.* (2019) and Lee *et al.* (2020) catalogs. In this way, I only use 125 of 349 foreshocks present in the catalog (it contains 149 since 4 July 2019 00:00 UTC). I am aware that an even more detailed foreshock catalog exists (Lee, *et al.* 2020), but its  $M_L$  scale does not agree with all the other catalogs (see Figure 9.2); I therefore did not consider this catalog.

### 2.3.1.2 Magnitude conversion ( $M_L$ to $M_w$ )

To not depend on the scaling break of the local magnitude,  $M_L$ , in high-resolution catalogs (Herrmann and Marzocchi 2021), I convert them to moment magnitudes,  $M_w$ , using two different relations: (i) an average European scaling relation by Grünthal *et al.* (2009), which is based on a polynomial fit using catalogs of different seismological agencies with most events having  $M_L > 1.5$  and  $M_w \gtrsim 1.5$ :

$$M_w = 0.53 + 0.646M_L + 0.0491M_L^2, \quad (2.1)$$

and (ii) a bilinear conversion based on numerical and theoretical proofs (Hanks and Boore 1984; Bethmann, *et al.* 2011; Liu, *et al.* 2020):  $M_w = 2/3M_L + C$  for  $M_L < 2-4$ . I calibrate the former by adding + 0.23 so that  $M_w$  and  $M_L$  are the same at  $\sim M 3.4$ ; for the latter, I assume that the scaling break (above which  $M_w = M_L$ ) occurs at  $M 3.3$ , hence,  $C = 1/3 M_{break} = 1.1$ . In

the main paper, I only show and refer to results based on the former relation (Grünthal, *et al.* 2009); results based on the second relation are reserved for the supporting information (Table 9.1).

### 2.3.1.3 *Magnitude–frequency distribution*

To estimate a meaningful  $b$ -value, the magnitude must be exponentially distributed (Marzocchi, *et al.* 2020). To satisfy this requirement, the preferred choice would be a statistical goodness-of-fit test for exponentiality with the Lilliefors test, which proved to be effective in high-resolution catalogs (Herrmann and Marzocchi 2021); however, this non-parametric method loses statistical power for small sample sizes (Marzocchi, *et al.* 2020) like in my case. Therefore, I determine the magnitude of completeness,  $M_C$ , with the conventional maximum curvature method (MAXC, Wiemer and Wyss 2000) with a correction of +0.2 (Woessner and Wiemer 2005). For increased robustness and reproducibility for this small sample size, I take the average of 105 bootstrap resamples. To guarantee comparability between  $M_L$  and their  $M_W$ -converted counterpart, I determined  $M_C^{MAXC}$  only once for  $M_L$  and converted it to  $M_W$ -units using the corresponding conversion relation.

I calculate the  $b$ -value and its error for all events above  $M_C^{MAXC}$  with a bias-free estimator (Tinti and Mulargia 1987; Marzocchi and Sandri 2009), which accounts for binned magnitudes. To estimate a  $b$ -value that is not biased by STI, I apply the  $b$ -positive method (van der Elst 2021) using magnitude differences between successive events,  $\Delta M$ . The  $b$ -positive method assumes that if the

magnitudes are exponentially distributed, also the positive magnitude difference,  $\Delta M^+$ , follows an exponential distribution with the same parameter (the  $b$ -value). Because  $\Delta M^+$  involves a larger event following a smaller one, it is minimally affected by short-term incompleteness—large events are always detected—thus providing an estimate of  $b$  that is far less biased than the classical GR approach. Hence, I calculate the  $b$ -positive estimate by applying the above bias-free  $b$ -value estimator solely on  $\Delta M^+$ , with the corresponding completeness level in  $\Delta M^+$  space being twice the discretization level (van der Elst 2021), i.e., magnitude binning.

#### 2.3.1.4 *Magnitude correlation coefficient and significance*

Similar to the  $b$ -value calculation, I quantify magnitude correlation only for magnitudes above the estimated  $M_C$ . To assess magnitude correlation, I explore the relationship between the magnitude,  $m_i$ , of the  $i$ -th event and the magnitude,  $m_{i+1}$ , of its consecutive event ( $i = 1, 2, \dots, n - 1$ , with  $n$  the number of events). I measure their linear relationship with the Pearson correlation coefficient, denoted as  $r$ , which varies between  $-1$  and  $1$ :

$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}}, \quad (2.2)$$

with  $x$  representing all  $m_i$ ,  $y$  all  $m_{i+1}$ , and  $\bar{x}$  and  $\bar{y}$  their mean, respectively. For comparison, I also determine the Spearman correlation coefficient, which measures monotonic relationships and is less sensitive to the presence of (magnitude) outliers. The main text and figures only report results based on

Pearson's  $r$ ; Spearman correlation results are reported in the Table [9.1](#). I perform a one-sided test with the null hypothesis  $r = 0$  (i.e., no magnitude correlation) and—assuming this null hypothesis is true—obtain a  $p$ -value that represents the probability to have a correlation equal to or larger than the observed  $r$ . In other words, the  $p$ -value quantifies how likely it is to observe  $r$  by chance from the data if there is no underlying magnitude correlation. I consider the magnitude as significantly correlated if the  $p$ -value is  $< 0.05$ .

#### *2.3.1.5 Creating a synthetic earthquake catalog*

I generate a synthetic earthquake catalog using the simpleETAS model of Mancini and Marzocchi (2024). Purposedly, I generate it for a generic seismic zone, Italy in this case, to make my results more generalizable. As a matter of fact, simpleETAS, as well as most ETAS models, assumes the spatial invariance of earthquake sequence features (except for models that have spatially varying triggering parameters), i.e., every earthquake sequence has the same basic features independently from where it happens (Stallone and Marzocchi 2019). Similarly, I assume that the spatial distribution of the background seismicity rate does not affect the earthquake sequence features. Moreover, also the simulated STI, which is described in “[Extracting synthetic sequences and applying short-term incompleteness \(STI\)](#)”, is applied to the synthetic catalog independently from where the earthquakes are located. These assumptions render specific spatial features of the earthquake catalogs as irrelevant for the purpose of this analysis. My only requirement is that the (incomplete) synthetic catalog should

contain a comparable number of earthquakes as the real catalog (in the same order of magnitude) to make the power of the statistical tests comparable.

#### 2.3.1.6 *Extracting synthetic sequences and applying short-term incompleteness (STI)*

I identify sequences in the synthetic earthquake catalog using the declustering method of Gardner and Knopoff (1974). To obtain individual sequences that are comparable with the real foreshock sequence, I only take events that are four orders of magnitude below a sequence's mainshock and apply short-term incompleteness (STI) as described in the following paragraph, and then select events temporally as described in the subsequent paragraph.

I impose STI by removing events that are likely to be undetected in real cases. The STI relation of Helmstetter (2006),

$$M_c(m, \Delta t) = m - 4.5 - 0.75 \log_{10}(\Delta t), \quad (2.3)$$

describes a temporally decaying completeness threshold at time  $\Delta t$  (in days) after an event with magnitude  $m$ . I determine  $M_c(m, \Delta t)$  for each event  $i$  with occurrence time  $t_i$ , align them to  $t = t_i + \Delta t$ , and superpose them, that is, I consider each event to impose its own STI (not only the largest event). The superposition of all individual  $M_c(m, t)$  yields a temporally varying completeness threshold,  $M_c(t)$  (see Figure 9.3). To avoid a hard cutoff, I “convolve”  $M_c(t)$  with the detection function of Ogata and Katsura (1993) as a function of magnitude:

$$F(M|\mu(t), \sigma) = \int_{-\infty}^M \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu(t))^2/2\sigma^2} dx \quad (2.4)$$

which is the cumulative distribution function of the normal distribution. Setting  $\mu(t) = M_C(t)$  would only correspond to a 50% detection rate (i.e., completeness) above  $M_C(t)$  and remove too many events that are likely detectable. For more realism, I set  $\mu(t) = M_C(t) - \sigma$ , which corresponds to a detection rate of  $\sim 84\%$  above  $M_C(t)$ .  $\sigma$  is assumed to be 0.2 (van der Elst 2021), which means that the catalog is 95% complete above  $M_C(t) + 0.13$ , and 99% complete above  $M_C(t) + 0.27$ . Since  $\mu(t)$  is close to the mode of the incomplete MFD, which can be estimated with the maximum curvature method (MAXC, Wiemer and Wyss 2000), these choices are consistent with the +0.2 correction of Wössner and Wiemer (2005) to derive  $M_C$  from the mode of the MFD. To remove undetectable events, I assign a uniform random probability to every event and exclude those with probabilities below  $F(M|\mu(t), \sigma)$ .

To have synthetic sequences with applied STI that compare to the foreshock sequence in the real catalog, I only keep 35 events that occurred before each of the sequences' mainshock and 100 events afterwards. Each of these sequences with applied STI span a certain time period, defined by their first and last event. The corresponding complete sequences (without STI) are composed of all earthquakes from the complete synthetic catalog that occur in those time periods. Finally, I normalize the magnitudes of each sequence to the  $[0, 4]$

magnitude range as in the real catalog by subtracting the sequences' mainshock magnitude and adding 4.0.

#### *2.3.1.7 Determining magnitude statistics of synthetic earthquake sequences*

To compare the  $b$ -value and magnitude correlation of the single real foreshock sequence against those of multiple synthetic sequences, I apply to each synthetic sequence (complete and incomplete ones) the same procedure that I perform for the real foreshock sequence: determine  $M_C$  with the MAXC method, only consider events with magnitudes equal or larger than this  $M_C$  and determine the  $b$ -value as well as the correlation coefficient. I determine the same properties for the synthetic sequences with STI using  $\Delta M^+$ , but with  $M_C$  in  $\Delta M$  space being twice the discretization level, i.e., 0.02. I then determine the distribution of  $b$ -values, the average correlation coefficient, and combine the  $p$ -values of the correlation test with Fisher's method.

For assessing the magnitude correlation, I also perform an alternative analysis: I first normalize the magnitudes of each sequence (separately for complete and incomplete ones) by subtracting their mean and dividing by their standard deviation. Then, I determine the (normalized) magnitude pairs  $(m_i^j, m_{i+1}^j)$  for all corresponding sequences  $j$  (like for the sequence-based analysis above) and combine them to a set of magnitude pairs  $\{(m_i^j, m_{i+1}^j)\}$  (Figure 9.4). (Same

procedure when using  $\Delta M^+$ .) This effectively performs one single Pearson/Spearman correlation test for all sequences combined.

### 2.3.2 Analyzing the southern California catalog and comparison with a synthetic earthquake catalog

#### 2.3.2.1 *Data selection and simulating a synthetic catalog*

We use the relocated earthquake catalog for southern California (Hauksson, *et al.* 2012), considering all earthquakes from 1 January 1981 to 31 December 2022.

To define a reasonable magnitude threshold for the analysis, i.e., completeness magnitude  $M_C$ , I use again the maximum curvature method (Wiemer and Wyss 2000) with a correction of +0.2 (Woessner and Wiemer 2005), which yields 1.5 ( $M_L$  scale).

For a comparison as in the sequence-based analysis, I create two synthetic catalogs using two different ETAS models: (i) simplETAS of Mancini and Marzocchi (2024) for Italy as described above (see “Creating a synthetic earthquake catalog”) and (ii) AftSimulator of K. Felzer for southern California (Felzer, *et al.* 2002), based on parameter values of Hardebeck *et al.* (2008). In the paper, I only show and refer to results using the former model; results based on the second model are reserved for the supporting information (see Table 9.1). To facilitate the comparison, I use the completeness magnitude of the real catalog ( $M_C$  1.5) as a lower magnitude limit. To create an incomplete version, I

apply STI as described in the corresponding “Data and Methods” subsection above, which yields a comparable number of events as the real catalog. As mentioned before, a comparable number is necessary to achieve a similar power of the statistical tests.

I identify individual sequences and their largest event (“mainshock”) in both real and synthetic catalogs as before using the declustering method of Gardner and Knopoff (1974). I then classified the sequences into four mainshock magnitude classes according to the magnitude of their mainshock:  $C_M = \{3.5 \leq m_M < 4.5, 4.5 \leq m_M < 5.5, 5.5 \leq m_M < 6.5, m_M \geq 6.5\}$ .

#### 2.3.2.2 *Moving average magnitude to explore the presence of STI*

To investigate how STI is influenced by earthquakes themselves, I obtain the temporal evolution of the average magnitude of earthquakes as follows:

- For each sequence, I only use events that occur after the mainshock (“aftershocks”) and determine their time difference to the mainshock;
- I stack all aftershock sequences belonging to a specific  $C_M$ ;
- For each stack, I calculate the moving average of the magnitude with a sliding window of 50 events at each event.

#### 2.3.2.3 *Magnitude correlation in earthquake sequences*

First, I select aftershock sequences in each  $C_M$  and apply three different magnitude thresholds  $M_C = \{1.5, 2.5, 3.0\}$  that acknowledge mine and other  $M_c$  found for southern California with various estimation methods

(Stallone and Marzocchi 2019; Godano, *et al.* 2022). For each sequence and as a function of these  $M_c$ , I determine the expected end of STI of its mainshock with the relation of Helmstetter *et al.* (2006) and split the sequence into two periods: before the expected end of STI (“STI period”), and after it (“post-STI period”); see Figure 9.3. For each period and each combination of  $C_M$  and  $M_c$ , I determine the correlation coefficient and corresponding  $p$ -value by combining (normalized) magnitude (or  $\Delta M^+$ ) pairs as described in a previous “Data and Methods” section. The number of events in each  $C_M$  of the real and incomplete synthetic catalog has the same order of magnitude, which allows us to get a comparable statistical power of the tests.

Then, for each of these sets, I determine the Pearson correlation coefficient  $r$  and  $p$ -value if  $n > 20$ . Each set of magnitude pairs is considered as significantly correlated if the  $p$ -value is  $< 0.05$ . I report the same quantities based on the Spearman correlation in Figure 9.5 and Figure 9.6 to verify the stability of the results.

I repeat this analysis for positive magnitude differences  $\Delta M^+$  and perform this whole procedure separately for the real catalog, complete synthetic catalog, and incomplete synthetic catalog with STI.

## 2.4 Results

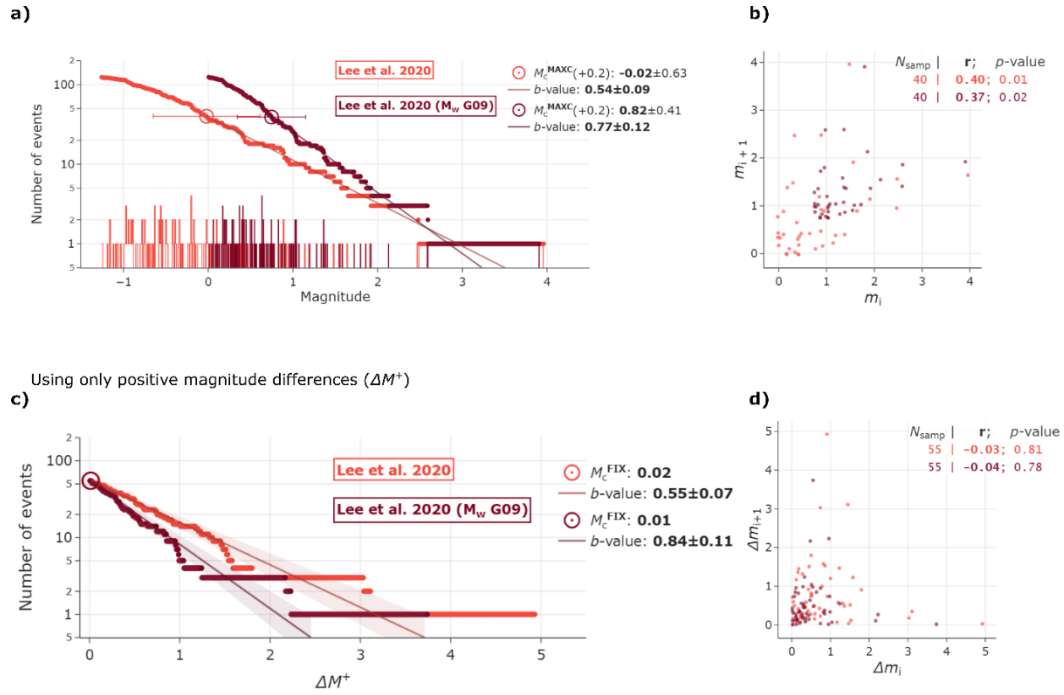
### 2.4.1 Ridgecrest: a remarkable foreshock sequence

In the following, I expand my analysis of the 2019 Ridgecrest foreshock sequence (Figure 9.1) using only the catalog with the most foreshocks (Lee, *et al.* 2020). Figure 2.1 reiterates that (i) the magnitude–frequency distribution (MFD) of the original local magnitude,  $M_L$ , reveals an extremely low  $b$ -value of  $0.54 \pm 0.09$  as estimated with a conventional approach (see “[Data and Methods](#)”); and (ii) the magnitude is significantly correlated, as indicated by a large coefficient ( $r = 0.40$ ) and a  $p$ -value  $< 0.05$  (see “[Data and Methods](#)”). To explore the physical meaning of these features, I consider the influence of two undesired effects in earthquake catalogs: the nonlinear scaling of  $M_L$  (already explored by Deichmann 2017), i.e., the departure of the MFD from an exponential-like Gutenberg–Richter relation (Herrmann and Marzocchi 2021), and STI (see “[Introduction](#)”) that remains undetected with conventional completeness estimation methods.

To address the first undesired effect, I convert  $M_L$  to moment magnitudes,  $M_W$  (see “[Data and Methods](#)”). Accordingly, the  $b$ -value markedly increases to  $0.77 \pm 0.12$ , albeit remaining far below the tectonic background  $b$ -value of around 1.0 (Figure 2.1a). This notable increase corroborates the existence of a nonlinear scaling of  $M_L$  that questions the meaning of the  $b$ -value in high-resolution catalogs (Herrmann and Marzocchi 2021). The magnitude conversion does not affect the presence of magnitude correlation (Figure 2.1b).

To address the second undesired effect due to undetected STI, I re-estimate the  $b$ -value using the  $b$ -positive method (van der Elst 2021).  $b$ -positive is based on using only positive magnitudes differences,  $\Delta M^+$  (see “[Data and Methods](#)”). Accordingly, Figure 2.1c shows that the  $M_W$ -based  $b$ -value estimate is further increased ( $0.84 \pm 0.11$ ) and not significantly different from 1.0 (the upper 95% confidence is 1.06). This implies that the  $b$ -value estimate with conventional methods is notably biased by undetected STI after only a moderate-sized event—the  $M_W 4.0$  foreshock. Interestingly, the  $b$ -value calculated for  $\Delta M_L^+$  remains very low ( $0.55 \pm 0.07$ ; Figure 2.1c), indicating that  $b$ -positive does not fix the bias introduced by the nonlinear scaling of  $M_L$ . Finally, using only  $\Delta M^+$  also affects the magnitude correlation: it is now virtually absent as indicated by  $r = -0.03$  with a  $p$ -value  $\gg 0.05$  (Figure 2.1d).

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**Figure 2.1** Magnitude statistics of the 2019 Ridgecrest foreshock sequence prior to the  $M_w 6.4$  event.

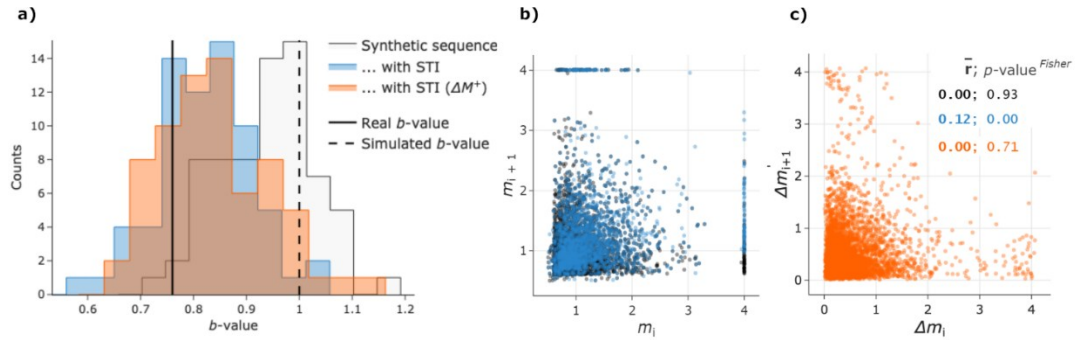
Light red represents the local magnitude ( $M_L$ ) as contained in the original catalog and dark red its conversion to moment magnitude ( $M_w$ ). Top panels (a and b) incorporate all events; bottom panels (c and d) are based only on the positive magnitude differences between successive events,  $\Delta M^+$  (b-positive method, van der Elst 2021). Left panels (a and c) show the magnitude–frequency distributions. The larger circle markers in panel (a) indicate the completeness magnitude calculated with the maximum curvature method (MAXC, see “[Data and Methods](#)”), and their horizontal whiskers the  $1-\sigma$  uncertainty from 100,000 bootstrap samples. The straight lines and shading represent fits of the Gutenberg–Richter relation; their corresponding  $b$ -value estimates with  $1-\sigma$  uncertainty are indicated in the legend. For confirmatory results based on an alternative  $M_w$  conversion relation (see “[Data and Methods](#)”), see [Table 9.1](#). Right panels (b and d) show scatter plots of the magnitude of every event,  $m_i$  (and  $\Delta m_i$ ), against the magnitude of its subsequent event,  $m_{i+1}$  (and  $\Delta m_{i+1}$ ) above the corresponding  $M_c^{MAXC}$ . The annotations in the upper right display the sample size, Pearson correlation coefficient  $r$ , and  $p$ -value (see “[Data and Methods](#)”). For confirmatory results based on the Spearman correlation coefficient, see [Table 9.1](#).

#### 2.4.2 The role of STI in similar synthetic earthquake sequences

To investigate the origin of magnitude correlation, I build a synthetic catalog (see “[Data and Methods](#)”) and extract sequences with similar properties as the Ridgecrest foreshock sequence—once without STI (i.e., complete) and once with applied STI (i.e., incomplete, see “[Data and Methods](#)” and Figure 9.7 for a timeline). The  $b$ -value distribution of the complete synthetic sequences (Figure 2.2, black histogram) is located around 1.0 as expected. Instead, the  $b$ -value distribution of the sequences with applied STI is significantly lower and contains the  $b$ -value of real foreshock sequence (Figure 2.2a, blue). For comparison, the  $b$ -value distribution for the synthetic sequences with STI based on the  $b$ -positive method (orange) is comparable to the one for complete sequences, confirming that  $b$ -positive can account for STI and provide a satisfactory  $b$ -value estimation (if STI is the only undesired effect in the MFD).

Since I sample the magnitude randomly from the exponential GR relation according to the magnitude-independence assumption, I expect no significant correlation between them; this is verified for the complete sequences in Figure 2.2b (black). But for the sequences with applied STI (blue), a significant magnitude correlation appears ( $\bar{r} = 0.11$ ;  $p\text{-value}^{\text{Fisher}} = 0.00$ ). Moreover, when considering only  $\Delta M^+$  (orange), the magnitude correlation is not significant anymore ( $\bar{r} = -0.01$ ;  $p\text{-value}^{\text{Fisher}} = 0.97$ ). Hence, this synthetic investigation confirms the analysis of the real sequence: that STI—even due to a

moderate-sized event and its triggered events—biases the  $b$ -value estimate and introduces a significant magnitude correlation.



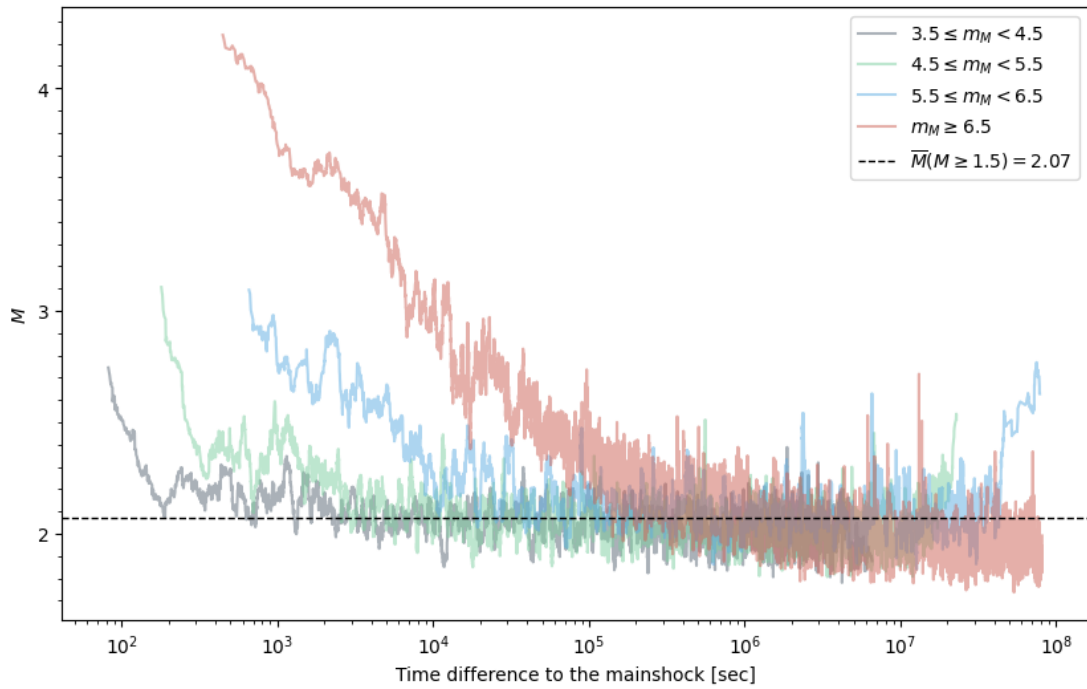
**Figure 2.2 Magnitude statistics of synthetic sequences.**

Black represents the synthetic sequences as simulated with ETAS (i.e., a complete catalog) spanning four orders of magnitude, blue with additional STI applied (see “[Data and Methods](#)”), and orange using only  $\Delta M^+$  of those sequences with applied STI. Panel (a): histogram of  $b$ -value estimates; panel (b and c): scatter plots as in Figure 2.1b and d ( $\Delta M^+$ ), respectively, for the synthetic sequences with applied STI. The annotations in the upper right of panel (c) display the mean Pearson correlation coefficient  $r$  among the sequences and the combined  $p$ -value using Fisher’s method. In Table 9.1, I also report the same quantity using the Spearman coefficient; the same Table 9.1 and Figure 9.4 additionally report  $r$  and  $p$ -values obtained by combining all (normalized) magnitude pairs of the sequences into two vectors,  $m_i$  and  $m_{i+1}$  (see “[Data and Methods](#)”).

### 2.4.3 Magnitude correlation in the southern California catalog and in synthetic earthquake catalogs

In the preceding section, I recognize that a conventional analysis is inadequate to identify STI satisfactorily in a foreshock sequence. To investigate whether this limitation is universal beyond relatively small and local sequences, I analyze the entire southern California catalog in terms of STI and magnitude correlation. I first explore the presence of STI empirically: Figure 2.3 shows the temporal evolution of the moving average magnitude of earthquakes following

mainshocks of various sizes (“mainshock magnitude class”,  $C_M$ ) above the estimated magnitude of completeness,  $M_C$ , of the whole catalog ( $M_L 1.5$ , see “Data and Methods”). For every  $C_M$ , the moving average exhibits a discernible decay, ultimately converging to the average magnitude,  $\bar{M}(M \geq M_c)$ , of the catalog. In other words, when the moving average converges to  $\bar{M}(M \geq M_c)$  STI is over, at least on average. These decays indicate that the intensity and duration of STI increase with the mainshock magnitude. But they also confirm that STI still exists after the smallest mainshocks considered in the analysis ( $3.5 \leq m_M < 4.5$ ) for several minutes.



**Figure 2.3 Investigating STI following mainshocks in the southern California catalog.**

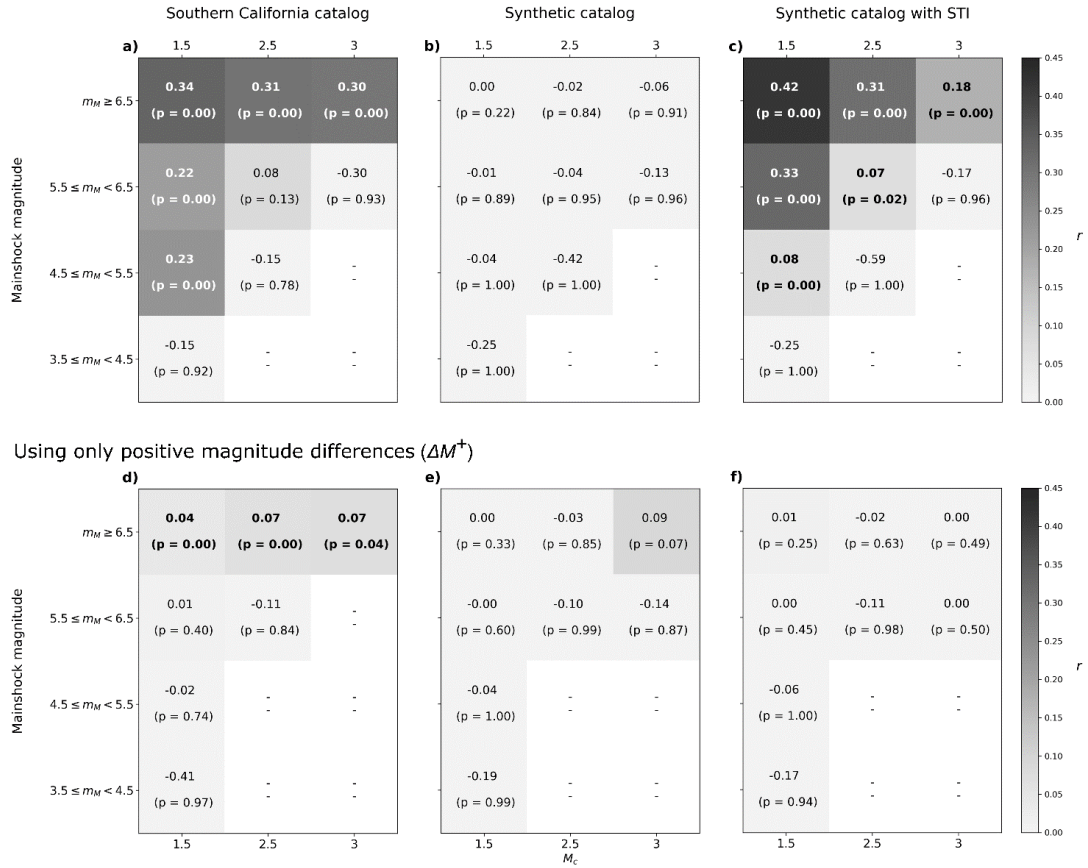
Each curve represents the average magnitude above  $M_C = 1.5$  in a sliding window of 50 events, comprising all sequences in the corresponding mainshock magnitude class  $C_M$  (see legend and “[Data and Methods](#)”). The dashed horizontal line represents the average magnitude above  $M_C$  of the catalog (the expected value for a complete catalog). For a comparison with the moving average calculated on the incomplete regional catalog see [Figure 9.8](#).

To investigate the characteristics of magnitude correlation, I calculate the Pearson correlation coefficient,  $r$ , and relative  $p$ -value, using the magnitudes of earthquakes that follow their mainshock (see “[Data and Methods](#)”). I investigate these properties for each set of sequences as function of  $C_M$  and  $M_C$  in three catalogs: the real catalog ([Figure 2.4a](#)), the complete synthetic catalog ([Figure 2.4b](#)), and the synthetic catalog with STI ([Figure 2.4c](#)). Additionally, I repeat this analysis using only positive magnitude differences,  $\Delta M^+$  ([Figure 2.4d–f](#)), which is supposed to circumvent STI (see “[The role of STI in](#)

similar synthetic earthquake sequences”). I perform this whole analysis in two separate temporal periods: (i) until the expected end of STI according to Helmstetter *et al.* (2006) given the mainshock magnitude of each individual sequence and  $M_C$  (“STI period”, Figure 2.4), and (ii) from the expected end of STI until the end of a sequence (“post-STI period”, Figure 2.5).

During the STI period, magnitude correlation in the real catalog tends to be more prominent and significant with increasing mainshock magnitude and decreasing completeness threshold (Figure 2.4a), as expected intuitively. The same trend can be seen for the synthetic catalog with applied STI (Figure 2.4c), with  $r$  and its significance being comparable. Only the complete synthetic catalog (without STI) does not show this trend (Figure 2.4b). When using only  $\Delta M^+$  (Figure 2.4d–f), the magnitude correlation is notably reduced for all subsets in the real and incomplete synthetic catalog; only in the real catalog it remains significant for the largest  $C_M$ . These behaviors in the STI period are replicated with the nonparametric Spearman correlation coefficient (Figure 9.5). Overall, these results strongly indicate that magnitude correlation is induced by STI, and not by any other effect.

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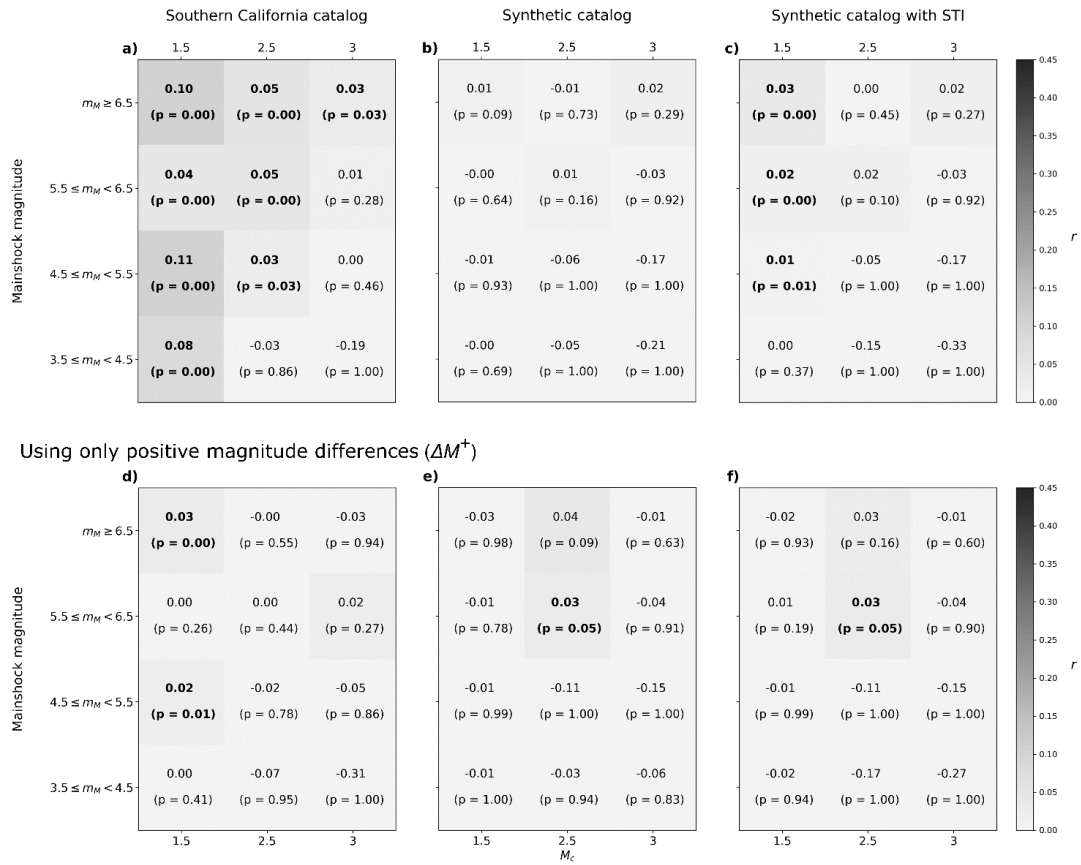
**Figure 2.4 Investigating magnitude correlation in the real and synthetic catalog during the expected STI period after mainshocks.**

The analysis is performed for three catalogs (see column titles), as function of mainshock magnitude class (x-axis of each panel), and magnitude of completeness  $M_c$  (y-axis of each panel). The STI duration was estimated for each sequence individually with the relation of Helmstetter et al. (2006) (see “[Data and Methods](#)”). Each cell in the heatmaps reports the Pearson correlation coefficient and the corresponding p-value (see “[Data and Methods](#)”); cells with p-value  $< 0.05$  indicate a significant magnitude correlation and are highlighted with bold text. Compared to the top panels (a–c), the bottom panels (d–f) are based on only positive magnitude differences  $\Delta M^+$ . For confirmatory results based on the Spearman correlation coefficient,  $r_s$ , see Figure 9.5, and based on a synthetic catalog generated with K. Felzer’s ETAS model, see Figure 9.9.

The post-STI period (Figure 2.5) gives some unexpected results: although magnitude correlation decreases in both the real (Figure 2.5a) and incomplete synthetic catalog (Figure 2.5c) as expected, the magnitude correlation remains

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higher in the real catalog—and more often significant—than in the incomplete synthetic one. Yet, both catalogs feature significant magnitude correlation at the smallest  $M_C$ . This higher correlation in the real catalog may indicate that the model of STI could underestimate the real incompleteness. When using only  $\Delta M^+$  (Figure 2.5d–f), most significant magnitude correlations disappear in both catalogs. The general behavior in the post-STI period has been verified with the Spearman correlation coefficient (Figure 9.6).



**Figure 2.5 Investigating magnitude correlation in the real and synthetic catalog during the expected post-STI period after mainshocks.**

For confirmatory results based on the Spearman correlation coefficient,  $r_s$ , see Figure 9.6, and based on a synthetic catalog generated with K. Felzer's ETAS model, see Figure 9.10.

I repeat the analysis for a synthetic catalog generated by K. Felzer's ETAS model (see Figure 9.9 and Figure 9.10), which confirms the trends shown in Figure 2.4 and Figure 2.5.

## 2.5 Discussion

I have found that magnitude correlation observed in real earthquake catalogs can be explained by short-term incompleteness (STI), which is not detected by conventional methods to estimate the completeness magnitude. I have underpinned this conclusion by comparing real seismicity with incomplete synthetic catalogs for two cases: a short foreshock sequence before the first large earthquake of the 2019 Ridgecrest sequence and an extensive regional catalog of southern California. I have shown that STI and magnitude correlation is pervasive and increases with mainshock magnitude, temporal proximity to the mainshock, and decreasing completeness magnitude. Properly removing STI using positive magnitude differences  $\Delta M^+$ , which I have borrowed from the *b*-positive method (van der Elst 2021), has also removed magnitude correlation in both cases. These findings indicate that magnitude correlation has no origin in underlying physical processes that could be used as precursory signals. In other words, I should have noticed if strong magnitude correlation was consistently caused by physical processes.

Although  $\Delta M^+$  mostly removed magnitude correlation, I notice that a low magnitude correlation remained significant in the STI period of the real catalog for the largest mainshock magnitude class  $C_M$  (Figure 2.4d), i.e., for the most

extreme cases of STI—but not in the incomplete synthetic catalog. I suggest that this remaining correlation is likely caused by assuming the same (unknown) level of completeness between magnitudes of successive events, which may be debatable at the beginning of the sequence. This effect should be explored further by examining the correlation structure of the  $\Delta M^+$  variable, which is beyond the scope of this paper.

I have also found that magnitude correlation persists beyond the expected duration of STI (Figure 2.5) as estimated with the common  $M_C(t)$  relation of Helmstetter *et al.* (2006) both in the real and incomplete synthetic catalog. But the magnitude correlation is much smaller than during the STI period, which further emphasizes the dominant role of STI in creating magnitude correlation. Still, magnitude correlation in the real catalog is more substantial than in the incomplete synthetic catalog, which suggests that the relation of Helmstetter *et al.* (2006) does not fully capture STI in the real catalog. Interestingly, magnitude correlation remained significant also for the largest  $C_M$  in the incomplete synthetic catalog at the lowest  $M_C$  level (Figure 2.5c). This observation can be explained with (larger) aftershocks imposing their own STI (see Figure 9.3)—an effect that certainly also persists in the real catalog and contributes to a sustained magnitude correlation in the post-STI period.

My findings are not bound to a specific region. Albeit focusing on southern California seismicity for the real case, my synthetic earthquake catalogs, which mirror the trends of the real catalog in terms of magnitude correlation, were

created with different models calibrated to different regions. This agreement emphasizes the stability and the generalizability of my findings to other crustal seismic regions.

My results demonstrate that magnitude correlation does not require any physical explanation; instead, it could be a more powerful indicator of STI than conventional completeness estimation methods. This circumstance also has an important implication for the  $b$ -value calculation and interpretation. Often, I may find “anomalous” low  $b$ -values even for sequences that appear to be complete according to conventional methods to estimate the magnitude of completeness. At the example of the 2019 Ridgecrest foreshock sequence, I have demonstrated that STI led to a biased  $b$ -value estimate, whose very low  $b$ -value originally caught my attention and stimulated this study. In addition, this  $b$ -value underestimation was further impaired by another catalog issue: the scaling break of  $M_L$  (Deichmann 2017; Herrmann and Marzocchi 2021; Bakun and Joyner 1984; Hanks and Boore 1984; Bethmann, *et al.* 2011; Munafò, *et al.* 2016). These biases highlighted that STI and a magnitude scaling break must be carefully considered when analyzing the MFD of earthquake catalogs. For an unbiased  $b$ -value in the presence of STI, the  $b$ -positive method (van der Elst 2021) provided an effective solution. However,  $b$ -positive is not a universal tool to eliminate other (artificial) magnitude artifacts that lead to a biased  $b$ -value, such as inconsistent magnitude scaling, magnitude estimation issues, and spatial incompleteness (Lippiello and Petrillo 2024). In fact,

applying  $b$ -positive on  $M_L$  still underestimates the  $b$ -value (Figure 2.1c). Those artifacts require dedicated solutions such as converting or homogenizing magnitudes and setting appropriate completeness thresholds.

## 2.6 Conclusions

My study reveals that observed magnitude correlation is caused, at least fundamentally, if not entirely, by STI. Even moderate-sized earthquakes induce a remarkable STI that existing completeness estimation methods fail to detect. Undetected STI biases statistical analyses and leads to a significant magnitude correlation and  $b$ -value underestimation. Moreover, STI in the real catalog appears to have longer durations than expected with a common  $M_C(t)$  relation, since magnitude correlation prolonged even after the expected end of STI. My findings imply that observed magnitude correlation is the most reliable indicator of STI, which might deem useful for reducing biases in statistical analyses of earthquake sequences. For the  $b$ -value estimation in particular, a significant magnitude correlation warrants the use of the  $b$ -positive method (van der Elst 2021). With STI driving magnitude correlation, magnitude correlation does not appear to be related to a preparatory phase of earthquakes.



# 3

## STRUCTURAL HETEROGENEITIES AND SPATIAL VARIATIONS OF SEISMICITY DRIVE TEMPORAL *B*-VALUE CHANGES

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I contributed to the conceptualization and design of the study, performed formal analysis and data investigation, developed methodology and software, participated in visualization of results, and co-wrote the original draft.

### 3.1 Abstract

For the 2016/2017 central Italy earthquake sequence, various studies reported spatiotemporal variations in the Gutenberg–Richter  $b$ -value, including its unexpected increase before the  $M_w$ 6.5 Norcia mainshock. Here, we investigate this specific observation with a combination of machine learning techniques. Before the mainshock, we identify two seismicity volumes with asynchronous activity, disparate fault orientations, and distinct  $b$ -values. Throughout the sequence, both structures maintain their distinct  $b$ -values; only when combined, the  $b$ -value apparently increases before the mainshock (and drops afterward). Our observation suggests that a temporal  $b$ -value variation in a large volume, or the entire extent of this sequence, originates from individual structures with distinct  $b$ -values being active at different times. More generally, temporal  $b$ -value variations may also reflect changes in the spatial distribution of seismicity besides other underlying processes. Our findings highlight that  $b$ -value interpretation must acknowledge the structural heterogeneity, such as associated fault segments and their orientations.

### 3.2 Introduction

Chapter 2 shows how some apparent anomalies in seismicity could derive from catalog incompleteness rather than real physical signals. This is crucial for the interpretation of temporal variations of the  $b$ -value.

Understanding the origin of  $b$ -value variability during an earthquake sequence has significant implications for earthquake forecasting but continues to be challenging. The current explanations are diverse: spatial  $b$ -value variations have been linked to different tectonic regimes and style of faulting (Gulia and Wiemer 2010; Kagan, *et al.* 2010; Petruccelli, *et al.* 2018; 2019; Schorlemmer, *et al.* 2005; Taroni and Carafa 2023) or changes in stress conditions, with low  $b$ -values indicating a critical stress condition (Schorlemmer, *et al.* 2005; Tormann, *et al.* 2014; Wiemer and Wyss 1997; 2002). It has been found that the  $b$ -value generally decreases before mainshocks and increases afterward (Gulia, *et al.* 2016; 2018; Tormann, *et al.* 2015) and those variations were proposed as an indicator for a larger impending earthquake (Gulia and Wiemer 2019), but it has also been found to increase before a mainshock (Herrmann, *et al.* 2022; Nanjo and Yoshida 2017). In addition, short-term aftershock incompleteness (STAI) of earthquake catalogs has been identified as another source of apparent  $b$ -value variability if not accounted for (Marzocchi, *et al.* 2020; Corrado, *et al.* 2025). More recently, spatiotemporal  $b$ -value variations have been resolved by various studies (García-Hernández, *et al.* 2021; Mirwald, *et al.* 2024). Specifically for the 2016/2017 central Italy

sequence, these variations have been shown to strongly depend on the selected seismicity volume (Collettini and Tinti 2025; Collettini, *et al.* 2022; Herrmann, *et al.* 2022), lithology, and style of deformation (Collettini and Tinti 2025). Despite these insights, a comprehensive understanding of how these factors interact and influence  $b$ -value variability during different stages of an earthquake sequence remains elusive. To address this gap, we pursue the complex relationship between  $b$ -value variability and seismicity. We explore whether the apparent temporal variations in the  $b$ -value during a sequence might instead reflect changes in the spatiotemporal distribution of seismicity, that is, by involving different faults with distinct characteristics. We focus on seismicity in central Italy during the 2016/2017 earthquake sequence. This sequence began in August 2016 with a  $M_W$ 6.0 earthquake (“Amatrice”) and was followed by further significant events: a  $M_W$ 5.9 (“Visso”), the mainshock  $M_W$ 6.5 (“Norcia”), and four  $M_W$ 5.0+ (“Campotosto”). While extensive research has explored complexity of the fault system and the potential seismogenic sources of this sequence (Basili, *et al.* 2008; Chiaraluce, *et al.* 2017; Convertito, *et al.* 2017; Sukan, *et al.* 2023; Valensise, *et al.* 2016; Vičić, *et al.* 2020; Vuan, *et al.* 2017; Walters, *et al.* 2018), debates continued about the configuration of the complex fault system responsible for these large earthquakes: discrepancies between surface observations and geophysical evidence have led to discussions on whether they are young and steep (Chiaraluce, *et al.* 2017; Villani, *et al.* 2018; Waldhauser, *et al.* 2021), old and nearly horizontal (Dziewonski, *et al.* 1981;

Ekström, *et al.* 2012; Pondrelli 2002; Zhong, *et al.* 2018), or a combination of both (Barchi, *et al.* 2021; Bonini, *et al.* 2019). Our study investigates the sequence from a different perspective. We examine the spatiotemporal evolution of the sequence close to the Norcia mainshock by identifying specific earthquake clusters and their corresponding geometric structures using a combination of various machine learning techniques. The double difference algorithm for hypocenter locations (Waldhauser and Ellsworth 2000) has significantly reduced locations uncertainties; since then, several studies have reconstructed active fault zone structures (e.g., Muzellec, *et al.* 2025; Ross, *et al.* 2020; Shelly 2020; Waldhauser, *et al.* 2004). Building on this progress, machine learning techniques have been increasingly applied to seismology over the past decade to diverse seismological problems, including the development of high-resolution earthquake catalogs, seismicity analysis, ground-motion prediction, and analysis of geodetic data related to crustal deformation (Kubo, *et al.* 2024). Specifically, the abundance of earthquakes in high-resolution earthquake catalogs requires dedicated methods to discern and analyze complex fault structures. For a cluster analysis of seismicity, a machine-learning-based approach is preferred for at least two main reasons: first, the vast amount of available data makes any operator-based analysis impractical; second, machine learning techniques are powerful in identifying intrinsic and hidden patterns in a reproducible manner with minimal bias. Specifically, we use the density-based clustering algorithms DBSCAN (Ester, *et al.* 1996) and

OPTICS (Ankerst, *et al.* 1999) for performing event clustering and analyzing spatially nested dense zones within clusters, respectively, as well as Principal Component Analysis (PCA, Pearson 1901) for inferring the planar geometry of those zones as fault surfaces. This combination of techniques has also been recently proposed for reconstructing the hierarchical segmentation of faults (Piegari, *et al.* 2024). For this sequence, various studies resolved the  $b$ -value in time and space with different spatiotemporal selection methods (Collettini and Tinti 2025; Collettini, *et al.* 2022; García-Hernández, *et al.* 2021; Gulia and Wiemer 2019; Herrmann, *et al.* 2022; Montuori, *et al.* 2016), generally finding a significant overall spatial and/or temporal  $b$ -value variability. We choose to focus my cluster-based analysis on the spatiotemporal evolution of seismicity close to the Norcia mainshock since the corresponding cluster featured a large and unexpected  $b$ -value increase prior to it (Herrmann, *et al.* 2022). We track the spatiotemporal evolution of this “Norcia cluster” throughout the sequence and characterize it in terms of magnitude distribution, which we compare using the  $b$ -value and a statistical test. In this way, we explore the complex relationship between seismicity and spatiotemporal variations of the  $b$ -value.

### 3.3 Data and Methods

#### 3.3.1 The Central Italy earthquake catalog

We use the high-resolution, machine-learning-based earthquake catalog from Tan *et al.* (Tan, *et al.* 2021), containing approximately 900'000 events and

covering one year of seismic activity from 15 August 2016 to 15 August 2017. For our analysis, we used the moment magnitude  $M_W$ , which is converted from local magnitude using an adapted scaling relation of Grünthal *et al.* (2009). For coherence with Herrmann *et al.* (2022) we selected events with  $M_W \geq 1.5$ , hypocentral depths  $\leq 12$  km, and within the spatial range of UTM zone 33, 330–370 km Easting, 4'690–4'790 km Northing (roughly 42.35°–43.25°N, 12.9°–13.4°E), resulting in a total of 76'055 events. In this way we reduce the computational time for the cluster analysis and only remove 2% of events that could act as noise.

To analyze the spatiotemporal evolution of seismicity clusters, we split the earthquake sequence into four periods defined by the four largest events—Amatrice, Visso, Norcia, and Campotosto:

1. Period I: between Amatrice and Visso (64 days, 11'976 events);
2. Period II: between Visso and Norcia (3.5 days, 6'615 events);
3. Period III: between Norcia and Campotosto (80 days, 42'009 events);
4. Period IV: after Campotosto (209 days, 15'440 events).

The locations of the four largest earthquakes are marked with large dots in Figure 3.1.

### 3.3.2 Machine learning approach

#### 3.3.2.1 *DBSCAN and OPTICS for spatial earthquake clustering*

Density-Based Spatial Clustering of Applications with Noise (“DBSCAN,” Ester, *et al.* 1996) is an algorithm designed to identify clusters of arbitrary shapes in large spatial data sets. It finds cluster solutions by treating a certain amount of data as noise. It takes two input parameters:  $\epsilon$ , representing the neighborhood distance around a point, and  $Z$ , the minimum number of points in a neighborhood. Once  $\epsilon$  and  $Z$  are defined, DBSCAN categorizes data points into three groups: core points, boundary points, and noise points. Core points have at least  $Z$  points in their  $\epsilon$ -neighborhood, boundary points are close to core points but have fewer neighbors, and noise points do not fit into either category. Adjusting  $\epsilon$  and  $Z$  act as a density threshold, influencing which points form clusters. Varying these parameters can lead to clustering smaller or larger groups of points, so choosing a sensible parameter combination is paramount for the subsequent analysis (Piegari, *et al.* 2022). We apply DBSCAN to identify spatial seismicity clusters within each of the four periods using only data that were available at the end of the considered time interval. The advantage of excluding previous and future events is that it selects the largest clusters individually for each period and allows for the analysis of their spatial and temporal evolution throughout the sequence. For each period, DBSCAN input parameters were chosen to achieve a solution within the so-called “crossover region” (Piegari, *et al.* 2022), which maximizes the number of large clusters while

ensuring that neither the largest cluster size nor the number of noise points exceeds 60% of the events in each period. This strategy balances a large number of clusters with the need to avoid over-clustering or excessive noise. Subsequently, we select the cluster closest to the Norcia mainshock in each period and refer to it as the “Norcia cluster.” To further characterize the spatial distribution of earthquake density within each cluster, we use OPTICS (“Ordering Points To Identify Clustering Structure”, Ankerst, *et al.* 1999), which captures the hierarchical clustering structure, to characterize the spatial distribution of earthquake density inside each cluster. OPTICS uses core distance (the minimum distance for a point to be a core point, like DBSCAN's  $\epsilon$ ) and reachability distance (how easily a point is reached from its neighbors, reflecting local density) to produce a reachability plot that visualizes each point's reachability distance. Valleys (low reachability distance) represent denser regions and indicate (sub)clusters (the deeper, the denser). Conversely, peaks represent transitions between different dense regions and indicate boundaries between (sub)clusters (the higher, the more separated).

### 3.3.2.2 *PCA for inferring planar surfaces*

PCA (Maćkiewicz and Ratajczak 1993) allows reducing the dimensionality of the data by retaining only the first few principal components that capture most of the variance. The principal components are the eigenvectors of the covariance matrix and are orthogonal to each other. In particular, the plane defined by the first two principal components is the best two-dimensional representation of the

data, as it contains projections with the largest variance. We use PCA to associate a planar surface with a cluster if two eigenvalues are significantly larger than the third one (details in [Text 2](#)). According to Tan *et al.* (2021), the high-resolution earthquake catalog includes 95% confidence ellipsoids for relative event locations, with median values of 36 m on the horizontal minor axis, 56 m on the horizontal major axis, and 87 m on the vertical axis. The high accuracy of the catalog allows us to neglect the effect of location errors in this process.

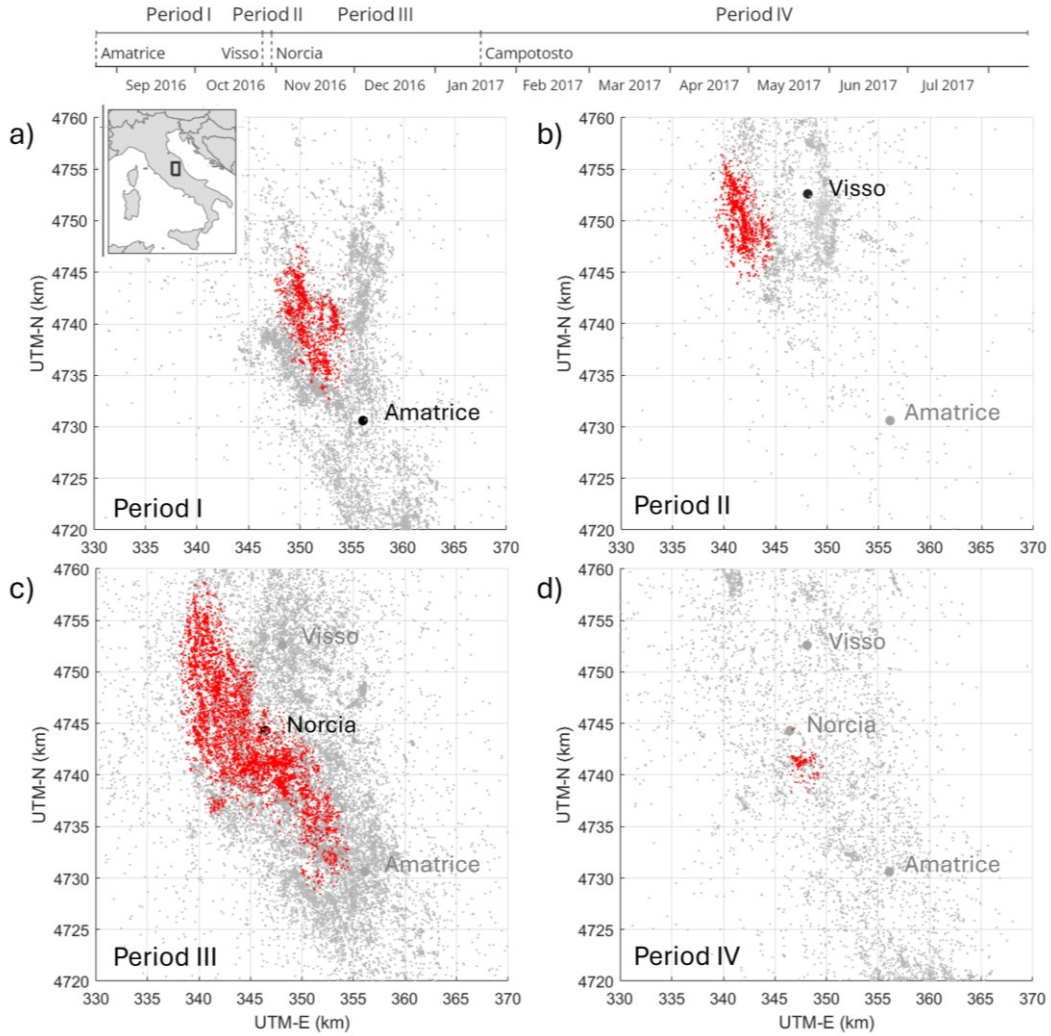
### 3.3.3 Earthquake magnitude statistics

We produce magnitude-frequency distributions (MFDs) for the Norcia cluster in each period. To determine the completeness magnitude ( $M_C$ ), we employ the Lilliefors test (Herrmann and Marzocchi 2021; Marzocchi, *et al.* 2020); it yields the lowest magnitude level for which an MFD can be considered exponentially distributed at a significance level of 0.1. Subsequently, we calculate the  $b$ -value and its error with a bias-free maximum-likelihood method (Marzocchi and Sandri 2003; Tinti and Mulargia 1987). To avoid the bias in  $b$ -value estimates caused by STAI (see “[Introduction](#)”), we exclude all events occurring in the incomplete portion of each period, following the time windows proposed by Herrmann *et al.* (2022): specifically, within 0.8, 0.6, 2.0, and 0.4 days after each main event, respectively. To assess whether the MFDs of individual spatiotemporal clusters are different, we apply the two-sample Kolmogorov–Smirnov (KS) test. The null hypothesis is that the MFDs of

individual spatiotemporal clusters come from the same underlying distribution, though the specific form of the distribution is unspecified. In our study, we adopt the standard practice (a.k.a. Neyman-Pearson approach) of rejecting the null hypothesis if the  $p$ -value falls below some pre-chosen significance level  $\alpha$ , which we take to be 0.05, that is, the 95% confidence level. To compare the MFDs across different periods, we only used events with  $M_W \geq 1.57$ , the maximum  $M_C$  among the clusters.

### 3.4 Results

Figure [3.1](#) illustrates the spatiotemporal evolution of the Norcia cluster. Details about the selection of DBSCAN input parameters and the characteristics of Norcia cluster are given in [Text 1](#) and Table [10.1](#).

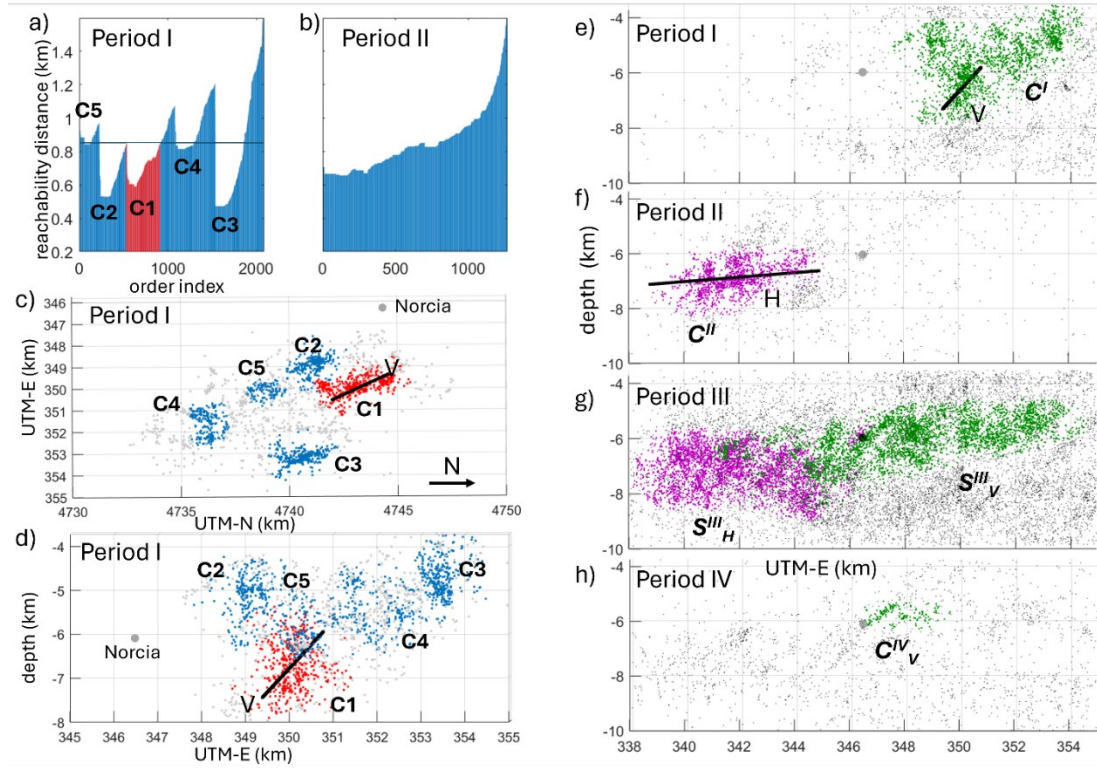


**Figure 3.1 Map view of the 2016/17 central Italy seismicity.**

The “Norcia cluster” highlighted in red. The main events—Amatrice, Visso, and Norcia—are represented by large black dots during their occurrence period and by dark grey dots afterwards. The Campotosto events occurred outside the area towards the South. For the corresponding depth sections, see Figure 3.2e-h.

In the first two periods, the Norcia cluster involves two contiguous seismic volumes without spatial overlap,  $C^I$  in Period I and  $C^{II}$  in Period II. Reachability plots (Figure 3.2a-b) characterize their internal structure: deep valleys in  $C^I$  indicate the presence of denser subregions, but not in  $C^{II}$ . This qualitative characterization provides evidence of  $C^I$  representing a fragmented structure, in

which seismicity is preferentially distributed in discrete zones rather than homogeneously like in  $C^{II}$ . To identify all five dense subregions in  $C^I$ , we perform DBSCAN with a threshold ( $\epsilon$ ) that individuates the five valleys (horizontal line in Figure 3.2a). The five resulting subclusters are shown in Figure 3.2c and d PCA for those subclusters reveals that only two (C1 and C5) satisfy the condition for dimensionality reduction; both are associated with high-angle planes. Details about the size and orientation of these planes are reported in [Text 2](#) and [Table 10.2](#). Since C1 is the largest subcluster, we choose C1 and its associated high-angle plane V (Figure 3.2c and d) as representative for the fault orientations inside the fragmented structure formed by  $C^I$ . This high-angle plane V has structural parameters consistent with those from literature: its dip of  $63^\circ$  and strike of  $-21^\circ$  (see [Text 2](#) and [Table 10.2](#)) align well with a dip of  $65^\circ$  and strike of  $340^\circ$  found by Walters *et al.* (2018) for a fault model that is slightly shallower (bottom depth 6 vs 8 km for high-angle plane V) and located slightly more toward southwest of plane V (centered at UTM-E 348.6, UTM-N 4736, see [Table 10.1](#) in Walters *et al.* 2018). The joint seismicity of clusters C2 and C5 provides similar results for the structural parameters at shallower depths (details in [Text 3](#)). Applying PCA to  $C^{II}$  reveals that seismicity in this more homogeneous structure is related to a single sub-horizontal plane H (Figure 3.2f).



**Figure 3.2 Machine-learning-based analysis of the Norcia cluster.**

*a, b) Reachability plots showing the event density distribution of the Norcia cluster in Period I ( $C^I$ ) and Period II ( $C^{II}$ ), respectively. The horizontal line in a) marks the threshold of the reachability distance used to identify subclusters. c, d) Map view and depth section of the five subclusters corresponding to the valleys in a). The thick black line represents high-angle plane  $V$ , which represents the principal orientation of subcluster  $C^I$ . e–h) Depth sections of the Norcia cluster for Period I, II, III, and IV, respectively. For corresponding map views see Figure 10.1. The thick black lines represent planes  $V$  and  $H$  related to  $C^I$  and  $C^{II}$ , respectively. Green and magenta dots indicate seismicity that is spatially associated with the structures formed by  $C^I$  and  $C^{II}$ , respectively, based on the proximity to those planes (see text). Grey dots represent earthquakes that occurred in each period within the spatial range between UTM-N 4730–4760 km (Longitude  $\sim 42.84^\circ \text{N} \pm 15^\circ \text{km}$ ). The Norcia mainshock is represented by a large black dot during its occurrence period and by dark grey before and afterwards.*

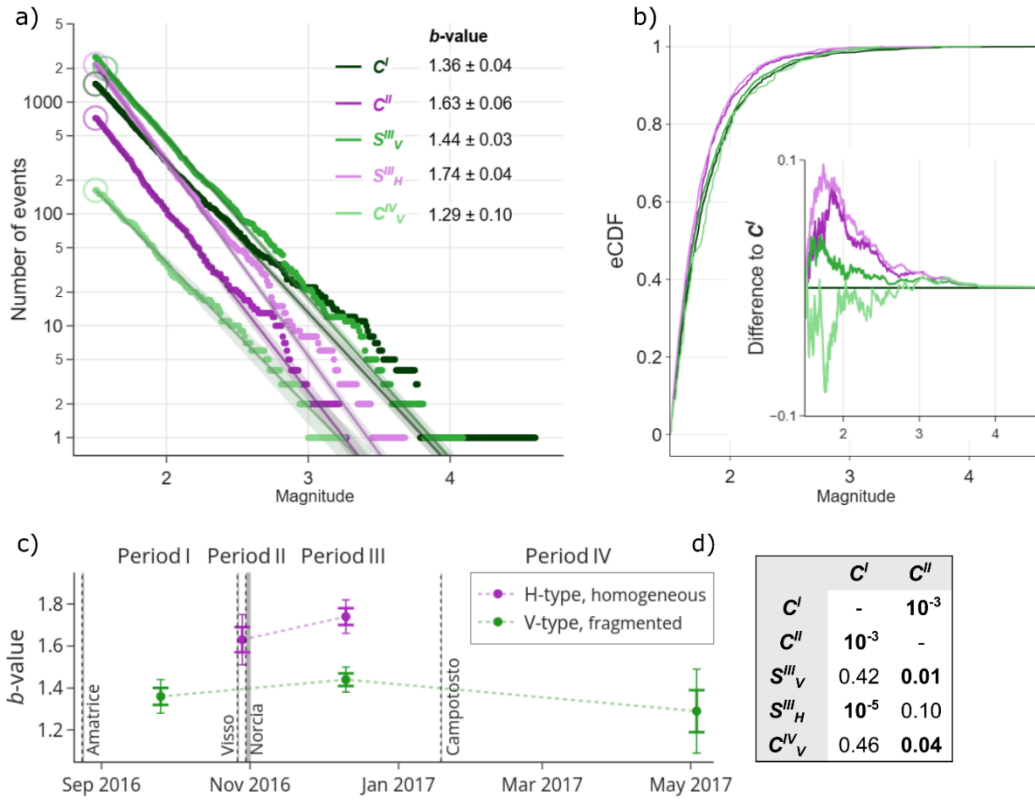
The Norcia cluster in Period III is the largest both in terms of event size and spatial extent, which apparently merges the two seismic volumes that were already previously active in Periods I and II ( $C^I$  and  $C^{II}$ ). Conversely, it is the

smallest cluster in Period IV; the largest seismicity clusters after the Campotosto events are located more southeastward. We associate seismicity of the Norcia cluster in Periods III and IV with one of the two structures formed by clusters  $C^I$  and  $C^{II}$  (high-angle fragmented structure and homogeneous sub-horizontal structure, respectively) by classifying events based on their proximity to planes V and H. From hereinafter, we refer to the former structure as V-type and the latter as H-type. In Period III, this classification results in two subsets of events,  $S_{III}^V$  and  $S_{III}^H$  (Figure 3.2g), which relate to the V- and H-type structure, respectively. In Period IV, all events are associated only to the high-angle fragmented V-type structure. After the Norcia mainshock, PCA is no longer applied, as my study focuses on the distribution of seismicity within pre-identified structures (shaped by  $C^I$  and  $C^{II}$ ). In addition, the Norcia cluster in period III largely encompasses the spatial volumes of both  $C^I$  and  $C^{II}$  (Figure 3.1 and Figure 3.2), suggesting that no significant new fault structures emerged post-mainshock. Figure 3.3 shows the magnitude statistics of the individual clusters  $C$  and subsets  $S$ . Regarding the  $b$ -value (Figure 3.3a and c), events associated with the V-type structure have similar  $b$ -values across different time periods (shades of green), as do those associated with the H-type structure (shades of magenta). Moreover, the H-type structure features consistently higher  $b$ -values than those associated with the V-type structure. Not treating both structures separately would lead to an apparent  $b$ -value increase

before the Norcia mainshock. Figure [10.2](#) shows the apparent  $b$ -value evolution throughout the sequence when both structures are combined.

To account for STAI in  $b$ -value estimation, we exclude the affected time windows. An alternative is the  $b$ -positive method, which estimates the  $b$ -value using only positive magnitude differences between successive earthquakes (van der Elst 2021). The  $b$ -value results are consistent with those obtained using the  $b$ -positive method (see Table [10.3](#)).

## STRUCTURAL HETEROGENEITIES AND SPATIAL VARIATIONS OF SEISMICITY DRIVE TEMPORAL B-VALUE CHANGES



**Figure 3.3 Magnitude statistics of the Norcia cluster.**

Green represents the V-type structure formed by  $C^I$  and magenta the H-type structure formed by  $C^{II}$ . a) Magnitude–Frequency Distributions (MFDs) for the two structures across periods. In the legend, C stands for cluster, S for subset; the superscripts refer to the period and the subscripts to the inferred internal fault structure. b) Empirical cumulative distribution function (eCDF) of magnitudes above  $M_W 1.57$  for the two structures across periods. The insert shows the difference between each eCDF and the eCDF of  $C^I$ . c) Temporal b-value variation in both structures. The b-value estimates with  $1\sigma$  and  $2\sigma$  error bars are centered inside each period; excluded STAI periods are indicated by vertical gray bars after each large event. For comparison, Figure 10.2b shows an apparent b-value variation throughout the sequence when both structures are not treated separately. d) p-values from the two-sample Kolmogorov–Smirnov test between the MFDs. p-values below 0.05 are highlighted in bold (see also Table 10.4).

Figure 3.3b and its insert compare the empirical Cumulative Distribution Function of the MFDs for the individual periods, while Figure 3.3d shows the  $p$ -values from their pairwise comparisons using the two-sample KS test. A  $p$ -value below 0.05 indicates that the MFDs are drawn from different distributions (with a probability of 5% to be wrong), whereas a  $p$ -value  $\geq 0.05$  suggests they are drawn from the same distribution. Accordingly, we can infer that events associated with the V-type structure have a similar MFD throughout the sequence, as do those occurring in the H-type structure. Additionally,  $p$ -values of the two-sample KS test indicate that MFDs associated with the V-type structure are significantly different from those of the H-type structure. These results confirm and strengthen the comparison based on the  $b$ -value. To test the stability of my results, we repeated our machine-learning-based analysis using different high-angle planes to characterize  $C^I$  and subsequently classify the seismicity of the Norcia cluster across periods based on this characterization. We note that a slight increase in the reachability threshold (horizontal line in Figure 3.2a) produces different clustering, first merging the very close valleys associated with clusters C1 and C2 and then including also the smallest one associated with cluster C5 (Figure 3.2a, c and d). With PCA, we retrieve high-angle planes that are different from V (details in Text 3 and Figure 10.3). An analysis performed with these planes confirms the results of the main analysis in terms of  $b$ -value evolution and  $p$ -values (Text 4, Figure 10.4, Table 10.5 and Table 10.6). We also investigated the  $b$ -value and  $p$ -values for Period III using

spatially more confined subsets with a buffer zone of 5 km in-between (see Figure 10.5); the  $b$ -value evolution (see Figure 10.6) and  $p$ -values (Table 10.7) are comparable to the main analysis.

### 3.5 Discussion and conclusions

We found that in the zone where the largest earthquake occurs, the temporal  $b$ -value variations are primarily driven by changes in the spatial distribution of seismicity. Following the Amatrice and Visso mainshocks, my analysis reveals that the volumes with the highest seismicity density are concentrated in two adjacent but non-overlapping zones, both located near the future hypocenter of the Norcia mainshock (highlighted clusters in Figure 3.1a, b, and Figure 3.2e–h). These zones exhibit distinct characteristics in terms of fragmentation, fault orientation, and associated magnitude distribution. The presence of a complex fault system illuminated by this sequence has already been established by many prior studies (see “[Introduction](#)”). During Period I, we found seismicity to be distributed across multiple small, dense clusters that identifies a high-angle fragmented structure (V) and  $b$ -values in the range  $1.36 \pm 0.04$ . In Period II, seismicity is distributed in a sub-horizontal structure (H) with higher  $b$ -values ( $1.63 \pm 0.06$ ). Our findings, even though they are based on a distinct analysis, align with those of Collettini *et al.* (2022) and Collettini and Tinti (2025), who show that both rock and fault rheology as well as differences in lithology and deformation style control spatial  $b$ -value variations. Specifically, they associate higher  $b$ -values with Triassic evaporites, which exhibit ductile-brittle rheology

that favors distributed seismicity, and lower  $b$ -values with carbonates, which display brittle behavior leading to small displacement faults and fractures. Our results confirm this pattern. The deeper part of the Norcia cluster in Period I (Figure 3.2d) corresponds to carbonate-rich zones with lower  $b$ -value, whereas those in Period II (Figure 3.2e) corresponds to evaporite-rich regions with higher  $b$ -values. We want to point out that the identified V- and H-type structures are also recognizable in Tan *et al.* (2021), see [Text 5](#) and [Figure 10.7](#) for more detail. We found that the MFDs of earthquakes associated with the two individual structures (V- and H-type) do not change throughout the sequence—they differ spatially but remain stable temporally (before and after the mainshock). In addition, both structures were active at different times before the mainshock. These observations combined explain the unexpected  $b$ -value increase that was observed for the larger volume/cluster before the mainshock (Herrmann, *et al.* 2022): mixing the behavior of individual structures led to an apparent  $b$ -value change (see also [Figure 10.2](#)). This explanation may also solve the temporal  $b$ -value variation that was generally found for this sequence in other prior studies (see “[Introduction](#)”), specifically the overall  $b$ -value decrease after the Amatrice event, its increase after the Norcia mainshock, and its subsequent apparent “recovery” to background levels. We propose that in this sequence the  $b$ -value largely (i.e., on first order) depends on the activated small-scale structures but does not have a significant temporal component. Consequently, the spatiotemporal variation of seismicity among different small-

scale structures with distinct  $b$ -values may primarily influence apparent temporal  $b$ -value variations in large volumes, or the entire extent of the sequence. As secondary effects, we cannot exclude minor temporal  $b$ -value variations inside the structures themselves (i.e., within the  $b$ -value uncertainties, see Figure 3.3a and c), which could be driven by temporal changes in rheology like fault healing processes (Bedford, *et al.* 2023; Fagereng and Beall 2021; Laurenti, *et al.* 2024; Lyakhovsky, *et al.* 1997; Rice and Cocco 2007). Therefore, our conjecture assigns a much smaller contribution to temporal changes in the stress state as the underlying cause, which is commonly assumed to correlate with the  $b$ -value. For interpreting temporal  $b$ -value changes, our findings highlight the important role of distinct fault segments as well as spatial and structural heterogeneities in interpreting temporal  $b$ -value changes. Differences in the physical characteristics of the faults themselves, such as heterogeneity, roughness, or stress variations across fault segments, play a significant role and affect the MFD. Worthy of note, we acknowledge that temporal variations in the stress field initially drive the reactivation of different faults. However, our structure decoupling shows that each fault structure has a distinct  $b$ -value, which can differ significantly. Thus, overall temporal  $b$ -value changes during a sequence may reflect this spatial variability, rather than univocally indicating stress changes—an often-used oversimplified interpretive assumption in seismology. In summary, the choice of cluster size is crucial for investigating  $b$ -value variability. If it is large enough to include seismicity across different

structures, such as those associated to the V- and H-type structures combined, temporal  $b$ -value variations may solely reflect a mixture of different geological features (e.g., in terms of rheology, lithology, deformation style, and/or faulting style) whose seismicity varies temporally—but not necessarily changes of the stress state. In other words, selecting a too large volume not only influences the spatial resolution of the  $b$ -value (Herrmann, *et al.* 2022), but also its apparent temporal evolution, potentially biasing subsequent interpretations. The previous cluster-based approach (Herrmann, *et al.* 2022) helped to identify appropriate reference volumes that are physically meaningful and defined objectively in a data-driven way, that is, using the seismicity distribution itself. Here we evolved this approach further with more machine learning techniques to study the volumes' evolution and internal structure; it offers the advantage of automation in identifying and characterizing reference volumes, potentially also in near-real-time applications. This capability allows us to illuminate active structures, study their evolution, characterize them structurally and in terms of associated  $b$ -values, and eventually aid in earthquake forecasting. Future studies will explore various types of multidimensional clustering to better understand and characterize  $b$ -value variability and also quantify the uncertainties associated with the PCA-derived fault orientations through a bootstrap resampling approach: for each hypocentral subcluster, we will generate a large number of bootstrap replicas and recompute the PCA on each sample. The resulting

ensemble of eigenvectors will allow us to derive empirical distributions for strike and dip, from which uncertainty bounds can be estimated.



# 4

## THE ROLE OF HEAT FLOW IN CONTROLLING THE GLOBAL VARIABILITY OF *B*-VALUE

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I contributed to the conceptualization of the study, curated and analyzed the data, carried out the investigation, developed methodology and software, created visualizations, and co-wrote both the original draft and the review/editing of the manuscript.

#### 4.1 Abstract

Earthquake magnitude-frequency distributions (MFD) exhibit significant space-time variations, which can provide critical insights into the physical processes driving seismicity. Understanding these variations is crucial for assessing seismic hazards and uncovering the physical processes driving earthquakes. One key parameter, the  $b$ -value, describes the relative proportion of small to large earthquakes and is thought to reflect factors such as stress conditions and fault properties. However, empirical evidence linking  $b$ -value variations to physical processes in real tectonic settings is still limited.

In this chapter, I present a global analysis showing that  $b$ -value is systematically higher in regions with elevated heat flow. This trend persists after accounting for first-order differences in tectonic setting or faulting style. This suggests that thermal conditions play a fundamental role—though not exclusive—in controlling earthquake size distributions, controlling the likelihood of large earthquakes in the different areas.

## 4.2 Introduction

Chapter 3 shows how the  $b$ -value variations could emerge from the superimposition of seismogenic structures with different properties, instead of real temporal changes in the stress state. That analysis, focused on a regional sequence, highlights how the geometry of the activated structure influences the magnitude statistics. This chapter widens this view, moving from a local to a global scale.

Space-time variations observed in the earthquake magnitude-frequency distribution (MFD) are particularly intriguing as they could provide important physical insights into the processes driving future earthquakes. These variations are typically analyzed as spatiotemporal changes in the MFD's key parameter, the  $b$ -value, which represents the slope of the distribution log-linear part (Kagan 2002, see " $b$ -values").

Such changes are often interpreted as signatures of the underlying physical processes, e.g., variations of differential stress (Amitrano 2003; Goebel, *et al.* 2013; Gulia, *et al.* 2018, 2020; Gulia and Wiemer 2010; Schorlemmer, *et al.* 2005; Tormann, *et al.* 2015; Scholz 2015), or as features of the lithology and geometry of the faults (Aki 1981; Hirata 1989; Herrmann and Marzocchi 2021; Collettini and Tinti 2025). Most of these physical interpretations stem from analog observations made during experiments but are rarely supported by solid empirical evidence from real tectonic earthquakes. Despite the apparent simplicity of calculating the  $b$ -value,

many space-time variations of the  $b$ -value may be attributed to space-time catalog incompleteness or the lack of constraints on MFD's upper bound (Kagan 1999; 2002; 2003; Marzocchi, *et al.* 2020; Herrmann and Marzocchi 2021; Corrado, *et al.* 2025).

At a global level, spatial variations in the  $b$ -value have been observed primarily in relation to the earthquake focal mechanism (e.g., Schorlemmer, *et al.* 2005; Petrucci, *et al.* 2018; 2019), while studies on the influence of tectonic setting presented mixed results. For instance, Bird and Kagan (2004) find significant changes across different tectonic settings only in the corner magnitude, not in the  $b$ -value, whereas Kagan *et al.* (2010) identify significant deviations of the  $b$ -value only in spreading ridges. Here, I aim to investigate the potential physical causes of such global variations of the  $b$ -value, examining the statistical correlation with a measurable physical quantity, the heat flow. Heat flow emerges as a good candidate due to its influence on  $b$ -value variations in volcanic regions and crustal areas with significant thermal variations, such as California (Enescu, *et al.* 2009; Nandan, *et al.* 2017; Manganiello, *et al.* 2023).

Several geophysical variables have been proposed to explain spatial variations in earthquake productivity and magnitude-frequency statistics, including strain rate, distance to active faults, and topographic loading (Bayliss, *et al.* 2025). Heat flow is therefore not expected to be the only potential control on  $b$ -value, but it is one of the few parameters that can be interpreted in terms of crustal thermos-mechanical state at a global scale. In this chapter, I focus specifically

on heat flow to test whether it exerts a first-order control on  $b$ -value patterns worldwide. A more complete multivariate evaluation, including tectonic setting and fault kinematics, is presented in Chapter 5.

## 4.3 Methods

### 4.3.1 Estimation of the completeness magnitude ( $M_C$ )

In this work, I use Taroni's (2023) method, which applies the Lilliefors tests (Herrmann and Marzocchi 2021), to check the magnitudes' exponentiality as implied by the Gutenberg-Richter law (Aki 1965). Taroni's (2023) method is particularly suitable for a catalog containing events that might have different  $b$ -values, as in the global CMT catalog. To avoid bias in the estimation, I split the catalog into two temporal windows, 1980-2003 and 2004-2023, because in 2004, there were improvements in the methods for event detection (Ekström, *et al.* 2012). I obtained  $M_C = 5.5$  in the first part and  $M_C = 5.1$  in the second part. Moreover, I also consider the short-term catalog incompleteness, which is present in the global CMT catalog (Kagan 2004; Iwata 2008), by increasing the completeness magnitude by 1.0 in the first 24 hours after each  $M_W 7.0+$  event (thus  $M_C = 6.5$  in the first part, and  $M_C = 6.1$  in the second part of the catalog, (vertical red "spikes" in Figure 4.1). To ensure the robustness of my results, I also consider conservative thresholds for completeness by increasing all the previous values by 0.2 and selecting the events accordingly.

For confirmatory results using even a more conservative estimation of the completeness, I also increased it by 1.5 in the first 48 hours after each  $M_w 7.0+$  event.

All the results obtained with this completeness are listed in Table 11.1.

#### 4.3.2 Estimation of the $b$ -value

Once the magnitude of completeness  $M_C$  is estimated, I compute the  $b$ -value of each sub-catalog using the method proposed by Taroni (2021), which considers the variability of the  $M_C$  with time. This method consists of subtracting to each magnitude of the dataset ( $M_i$ ) the value of the completeness magnitude at that time ( $M_C(t)$ ); the quantity  $X_i = M_i - M_C(t)$  can be used in the classical maximum-likelihood estimation for the  $b$ -value and for its related uncertainty  $\sigma$  (Aki 1965). If I consider the correction for the finiteness of the sample ( $n$  is the number of events in the dataset), I obtain (Marzocchi, *et al.* 2020):

$$\hat{b} = \frac{\frac{n-1}{n}}{\ln(10) \left( \frac{\sum_{i=1}^n X_i}{n} \right)} \quad (4.1)$$

$$\hat{\sigma}_{\hat{b}} = \frac{\hat{b}}{\sqrt{n}} \quad (4.2)$$

In my case, CMT magnitudes are derived directly from seismic moment and retain full decimal precision. As a result, no magnitude binning is used and no binning correction is required.

I underline that in this study, the  $b$ -positive method of van der Elst (van der Elst 2021) cannot be used because here as in Chapter 2, because the completeness magnitude decreases with time (after 2004).

Moreover, the applicability of the  $b$ -positive estimator requires that earthquake pairs share a similar level of completeness, which is only ensured when events occur within a limited spatial range. If earthquakes are too far apart, differences in network coverage can lead to distinct completeness magnitudes, thereby biasing the estimate. For this reason, the method imposes a spatial constraint  $d_{ij} < d_R$ , where  $d_{ij}$  is the inter-event distance and  $d_R$  the maximum radius over which completeness can reasonably be assumed constant (Lippiello and Petrillo 2024).

For the estimation of the  $b$ -value along with the corner magnitude, i.e. the two parameters estimation of the tapered Gutenberg-Richter distribution, I used the method of Taroni *et al.* (2021).

In this approach, the tapered Gutenberg-Richter is expressed in terms of seismic moment, which corresponds to a tapered Pareto distribution with two unknown parameters: the slope  $\beta$  (related to the  $b$ -value) and the corner moment. The key feature of the method is that it allows for a time-varying completeness threshold. For each event, the probability density function is evaluated using the completeness moment that applied at the time of its occurrence. The total log-likelihood is obtained by summing the contributions of all events, each referenced to its specific completeness level.

The parameters are estimated through a minimum likelihood search over a grid of possible  $\beta$  and corner-moment values, which yields both the maximum likelihood estimates and the full shape of the log-likelihood surface. Uncertainties are derived using the profile-likelihood method, by identifying the contour of the log-likelihood function corresponding to the confidence level.

### 4.3.3 Significance of $b$ -value differences

To determine whether there is a statistically significant difference between  $b$ -values, I use the two-sample Utsu test (Utsu 1966), which has been commonly adopted in several  $b$ -value studies and can be applied in the case of a magnitude of completeness changing with time (Taroni 2021).

We initially set a significance level of 0.01 to adopt a conservative criterion for statistical testing (reduce the chance of falsely rejecting the null hypothesis). Then, to account for multiple tests, I adjust the significance level to  $0.01/N$ , where  $N$  represents the number of tests conducted (Bonferroni 1936), in my case  $N = 4$ . Results with  $p$ -values below this adjusted threshold are marked in bold, indicating significant differences at this level.

### 4.3.4 Other statistical tests

To compare the heat flow distributions for events in different tectonic environments, I used the classical Mann-Whitney (MW) statistical test; to compute the correlation between the  $b$ -value and heat flow, I used the Pearson correlation coefficient; for the  $b$ -value comparison between two groups, I also

used the two-sample Kolmogorov Smirnov test (all these tests can be found in Gibbons and Chakraborti 2003). In all these cases, I use the Bonferroni correction (Bonferroni 1936) to account for multiple tests.

### 4.4 Data

#### 4.4.1 Catalog and heat flow model

In this work, I used the global CMT catalog (Dziewonski, *et al.* 1981; Ekström, *et al.* 2012) from 1980 to 2023, with a maximum depth of 50 km (Schorlemmer, *et al.* 2005); I assign each event to a specific tectonic environment according to Kagan *et al.* (2010). who identify four main tectonic zones: plate interior, active continent, ridge, and trench. I chose to omit results from the plate interior zone due to an insufficient amount of data, which prevented reasonable statistical analyses. Using the information of the focal mechanism contained in the CMT catalog and according to Anderson's theory (Anderson 1905) and the Aki-Richards (Aki and Richards 2002) convention, I classify events with a rake of  $[-135, -45]$  as normal, those with a rake of  $[45, 135]$  as reverse, and the rest as strike-slip. I then assigned the heat flow value according to the worldwide ( $2^\circ$  equal area grid) model of Davies (Davies 2013) to each earthquake using bilinear interpolation over the four nearest values of the Davies model to each epicenter.

In addition, I implemented a complementary selection procedure to ensure that only reliable heat flow information is considered. For each grid cell of the Davies model, I calculated the relative error as the ratio between the reported

uncertainty and the mean heat flow value. Cells with a relative error lower than the median were retained, while those with larger uncertainties were excluded. During the assignment of heat flow values to earthquakes, I again considered the four nearest cells; if at least one of them had been excluded due to large uncertainty, the corresponding event was discarded. Otherwise, the heat flow was computed as an inverse-distance weighted average of the four selected values. All analyses were repeated following this procedure, giving more weight to earthquakes associated with reliable heat flow estimates and reducing the potential influence of poorly constrained values.

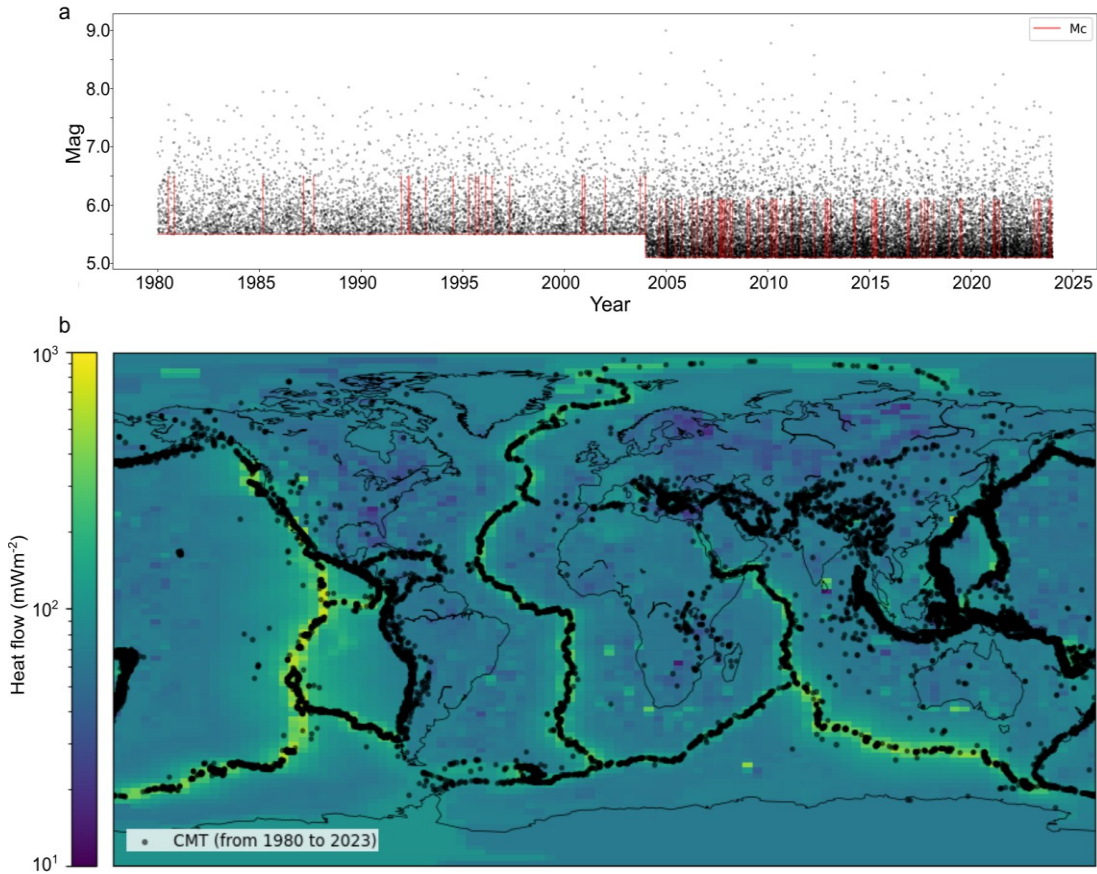
All the results obtained with this configuration are listed in Table [11.2](#).

## 4.5 Results

We consider the events provided by the Global CMT (Dziiewonski, *et al.* 1981; Ekstrom, *et al.* 2012), which represents one of the most homogeneous existing seismic catalogs. I pay special attention to the completeness of the earthquake catalog, as data incompleteness can significantly bias the estimation of the  $b$ -value. To address this issue and ensure unbiased estimation of MFD parameters, I calculate the completeness magnitude through time with different methods (see “[Methods](#)”), accounting for both changes in detection systems (Ekstrom, *et al.* 2012; González 2024) and potential short-term variations (Iwata 2008).

The procedure yielded a time-varying completeness magnitude (Figure [4.1a](#)) and led to a complete and homogeneous worldwide catalog, conditional on

time-varying magnitude threshold, from 1980 to 2023. Limiting to a maximum depth of 50 km (the incompleteness is directly proportional on the depth, Schorlemmer, *et al.* 2005; Petruccelli, *et al.* 2019), the catalog contains a total of 22'475 seismic events (Figure 4.1b).

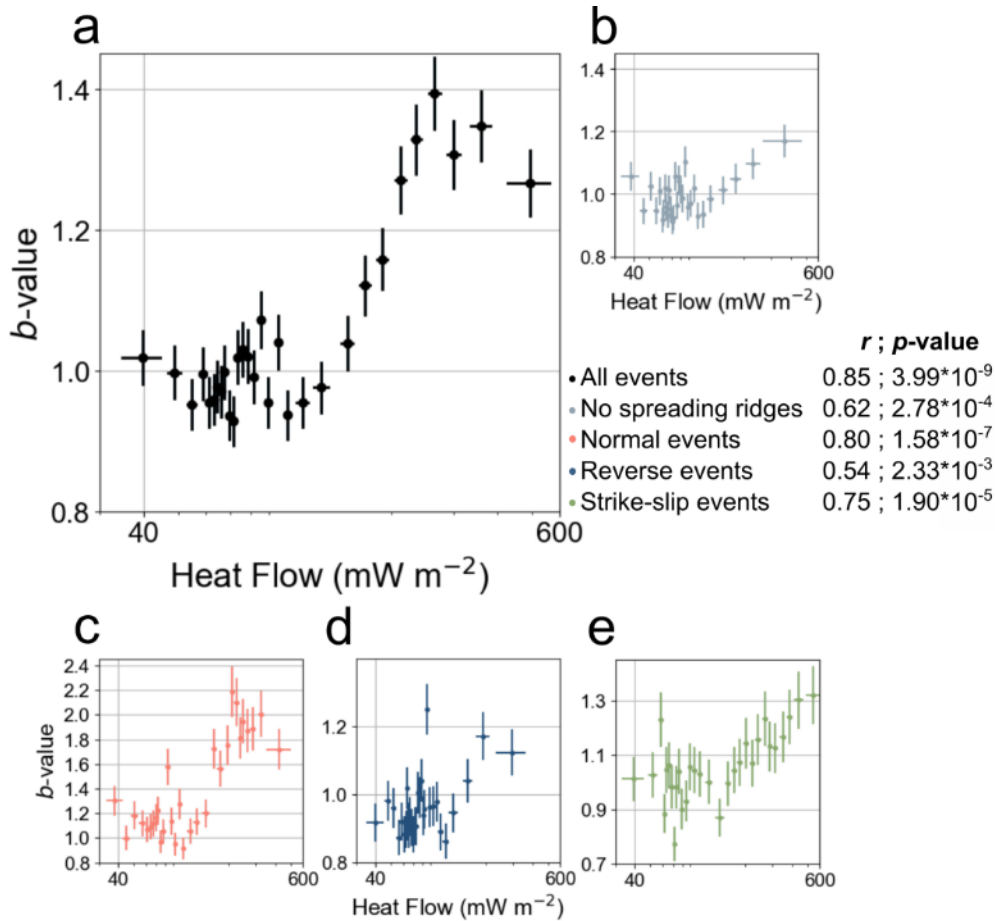


**Figure 4.1 Temporal and spatial distribution of the events.**

*a) Timeline of the events of the CMT catalog above the completeness magnitude ( $M_C$ ; red line); b) Distribution of the epicenters of the CMT catalog (Dziewonski, *et al.* 1981; Ekstrom, *et al.* 2012) of the events with a magnitude above the  $M_C$  overlain onto the heat flow model (Davies 2013). For comparison with a more conservative  $M_C$  see Figure 11.1.*

To introduce the heat flow variable in my computation, I quantify the local heat flow in the epicentral area of each event in the CMT catalog using the global heat model from Davies (2013) (see “Methods” for details and Figure 4.1b).

The MFD is then quantified by grouping the events with similar heat flow, independently from their location, and then estimating the Gutenberg-Richter  $b$ -value (see “Methods”). I identify a significant global correlation between the  $b$ -value and heat flow (Figure 4.2a), with higher  $b$ -values for higher heat flows.



**Figure 4.2 Correlation between  $b$ -value and heat flow.**

a) Considering all the events in the catalog above the completeness magnitude ( $M_C$ ); b) Excluding events that occurred in spreading ridges. For confirmatory results obtained using a more conservative estimation of the  $M_C$  and a different number of intervals, see Figure 11.2; c-e) Considering all the events and grouping them according to the focal mechanism (red for normal events, blue for reverse events and green for strike slip events). For confirmatory results obtained using the second solution of the CMT, a more conservative estimation of the  $M_C$  and a different number of intervals see Figure 11.3 and using a more conservative estimation of the  $M_C$  and a different number of intervals, see Figure 11.4.

Since the heat flow distributions in the different tectonic environments (Bird 2003) are significantly different from each other (see “Methods”, Table 11.3 and Figure 11.5), this result would provide a potential physical explanation for the observations that *b*-values are significantly different in the different tectonic environments (Kagan, *et al.* 2010; Bird and Kagan 2004). In spreading ridges, the heat flow is particularly high, but spreading ridges are also characterized by a relatively young and thin crust, which may limit the maximum magnitude and impact the *b*-value (Laske, *et al.* 2013; Bird and Kagan 2004). To reduce this circular argument and to investigate if the heat flow is the main driver, independently from these peculiar conditions of spreading ridges, I repeat the same analysis in two other conditions: i) by excluding all the events occurring along spreading ridges (Bird 2003), and ii) by adopting a tapered Gutenberg-Richter distribution to minimize the impact of potential shortages in large magnitudes due to a thin crust. In both cases, the trend remains similar, excluding the possibility that the correlation is only driven by events in spreading ridges (Figure 4.2b) or by a potential shortage of large events. However, these tests do not rule out the possibility that seismogenic thickness plays a role, given its strong covariance with heat flow on the global scale.

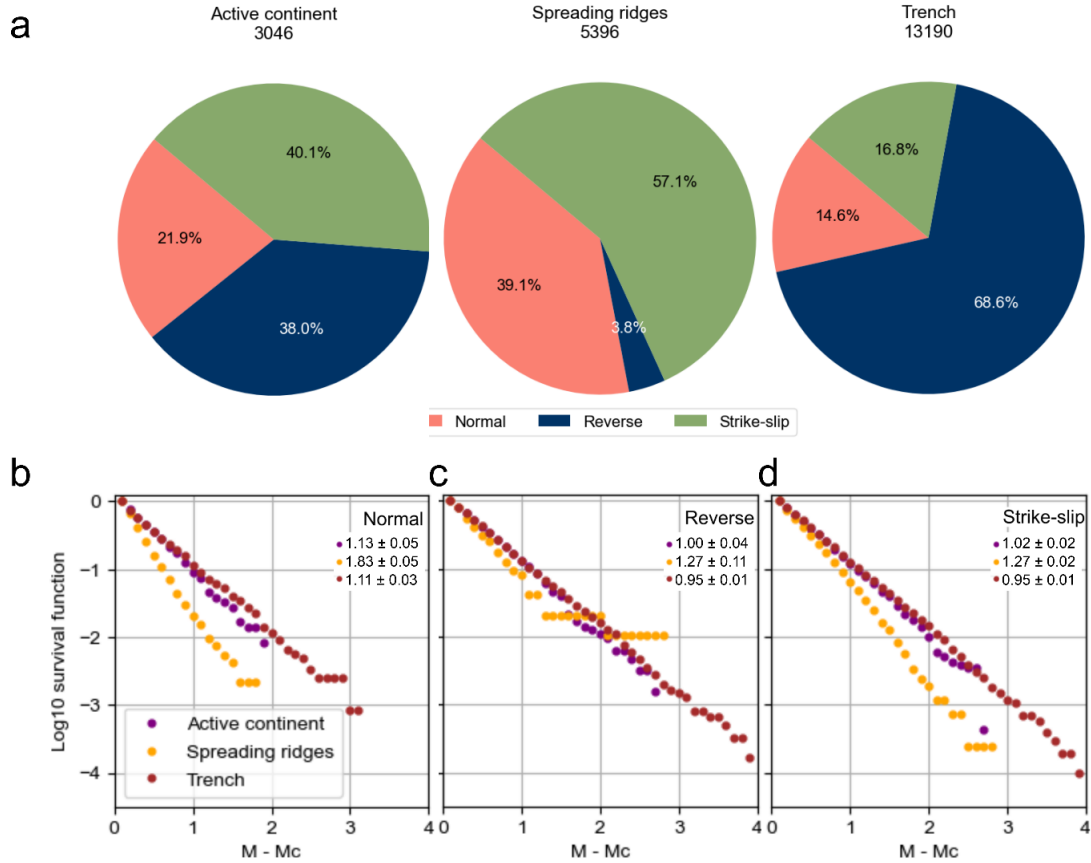
Still, this finding suggests that variations in heat flow may influence the variation of *b*-values independently from the tectonic settings.

These results are partially consistent with the findings of Cheng *et al.* (2020), who, using a different methodological approach, identified a nonlinear relationship between heat flow and earthquake magnitude distribution, with higher  $b$ -values sometimes being associated with higher heat flow.

To strengthen my analysis, I divide the magnitudes into two groups based on mean heat flow: one for values below  $132 \text{ mWm}^{-2}$  and one for values above this threshold (Figure 11.6). I then employ two statistical tests (see “Methods” and Figure 11.6 legends) to compare the MFDs and the  $b$ -values between the two groups, finding that MFDs and  $b$ -values are significantly different (the statistical test is rejected). Still, even when excluding events from spreading ridges, the two distributions remain consistently different.

The observed trends also explain the  $b$ -value variations as a function of the focal mechanism. This variation is usually interpreted as the effect of the stress that changes systematically between different faulting regimes (Schorlemmer, *et al.* 2005; Petrucci, *et al.* 2019). However, faulting styles are not uniformly distributed in the different tectonic environments (Figure 4.3a), which are characterized by different  $b$ -values (Figure 4.3b) and by different heat flows (Figure 11.5 and Table 11.3), with higher  $b$ -values in spreading ridges where normal faults are prevalent relative to other tectonic environments. As above, to overcome this circular argument and to investigate if the heat flow is the main driver, I repeat the analysis by grouping the events for focal mechanisms (this time using fitting a tapered Gutenberg-Richter), using the

three main faulting styles: normal, reverse, and strike-slip. I find that the significant trend between  $b$ -value and heat flow still holds for all the main faulting mechanisms (Figure 4.2c-e), showing that dependence applies to all individual focal mechanisms and goes beyond any direct dependence between the focal mechanism and  $b$ -value.



**Figure 4.3** Distribution of focal mechanisms in each tectonic environment and their MFDs.

Panel a) Percentages of occurrence of normal (blue), reverse (green), and strike-slip (red) events in each tectonic environment. The total number of events in each environment is at the top of each chart. For confirmatory results based on the second solution of the CMT and using a more conservative completeness magnitude ( $M_C$ ), see Figure 11.7. Panels b-d) MFD for each focal mechanism grouping according to the tectonic environment (Bird 2003). The  $b$ -values estimated with the tapered GR are listed in the top-right corner. For confirmatory results based on the second solution of the CMT and using a more conservative  $M_C$ , see Figure 11.8.

#### 4.6 Conclusions

Our results highlight the complexity of physical factors influencing the earthquake MFD. The global analysis suggests that the heat flow plays a major role in explaining the observed variability in  $b$ -values, with high  $b$ -values

systematically associated with high heat-flow conditions. This relationship persists across a range of tectonic settings and faulting styles, indicating that thermal structure is an important—but not exclusive—control on the size distribution of earthquakes.

It is important to emphasize that heat flow is unlikely to be the only relevant covariate: other factors such as strain rate, crustal thickness, distance to active faults, or large-scale tectonic deformation have also been shown to influence seismicity rates and magnitude–frequency statistics (e.g., Bayliss, *et al.* 2025).

In fact, heat flow and crustal structure are themselves strongly correlated at the global scale. Regions with high heat-flow tend to have a young and thermally thinned lithosphere, which naturally reduces the seismogenic thickness and limits the maximum magnitude. This makes it difficult to fully disentangle a direct thermal control on the  $b$ -value from an indirect effect mediated by the depth extent of the brittle layer. Testing these two hypotheses would require a dedicated comparison between  $b$ -values, heat-flow, and seismogenic thickness, ideally within a multivariate framework. Such analyses lie beyond the scope of this chapter, but the strong covariance between heat flow and crustal structure suggests that both mechanisms may be contributing to the observed trend.

In this chapter we focused specifically on heat flow, because it provides a direct proxy for the thermo-mechanical state of the crust at a global scale, and because laboratory and regional studies have long suggested a connection between thermal conditions and  $b$ -value variations.

Our results also show that the observed trend is not simply governed by the lack of large events in high-heat flow regions. Instead, the spatial patterns suggest that, within similar tectonic environments, differences in the thermal regime are associated with systematic differences in  $b$ -value. This is consistent with previous observation in volcanic regions (Farrell, *et al.* 2009; Rodríguez-Pérez, *et al.* 2021; Wyss, *et al.* 1997), where extremely high heat flow can produce a very thin seismogenic crust and, when combined with high deformation rates, can lead to a characteristic MFD (Main 1987). It is also consistent with laboratory rock deformation experiments (Warren and Latham 1970).

One key implication is that the high  $b$ -values associated with high heat-flow zones lead to a relatively low number of very strong events in these areas, as supported by the observations derived from analyses of worldwide catalogs during the last 120 years (Pacheco and Skyes 1992; Ekström, *et al.* 2012, see Figure 11.9). This applies across all tectonic regimes, providing a general conceptual framework to explain the relatively low frequency of large earthquakes observed both in spreading ridge areas compared to other tectonic environments (Kagan, *et al.* 2010; Taroni, *et al.* 2021) and in certain subduction areas compared to other subduction areas (Marzocchi, *et al.* 2016).

Overall, this chapter provides new insights into the physical drivers of  $b$ -value variability, emphasizing the central role of the thermal structure of the crust. At the same time, the results highlight the need to consider multiple covariates when interpreting spatial patterns in the MFD. The integration of heat flow with

tectonics and kinematics—developed further in Chapter 5—offers a pathway for improving seismicity models and enhancing the interpretation of *b*-value variations for hazard forecasting and risk mitigation.



# TECTONIC SETTING AND FAULT KINEMATICS JOINTLY INFLUENCE THE GLOBAL EARTHQUAKE MAGNITUDE- FREQUENCY DISTRIBUTION

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I contributed to the conceptualization of the study, curated and analyzed the data, carried out the investigation, developed methodology and software, created visualizations, and co-wrote both the original draft and the review/editing of the manuscript.

## 5.1 Abstract

The magnitude-frequency distribution (MFD) of earthquakes gives information about the statistical behavior of seismicity, and variations of the slope of this distribution—the  $b$ -value—are often interpreted as proxies for physical changes, such as variations in stress conditions. In Chapter 4, I showed that one first-order driver of this variability is the heat flow, but when considering the spatial variability of the MFD, two other main interpretations have been proposed to explain its primary drivers: some studies emphasize the role of large-scale tectonic environments (e.g., spreading ridges, trenches), while others highlight the role of fault kinematics. In this chapter, I make a review of those two interpretations, performing a global-scale analysis of the MFD for shallow earthquakes recorded in the Global CMT catalog, classifying events according to both tectonic environment and faulting style. I estimate completeness magnitudes and apply both the unbounded and the tapered Gutenberg–Richter model to jointly compute  $b$ -value and corner magnitude. I show that  $b$ -values vary significantly not only between tectonic environments but also within them, depending also on fault kinematics. However, apart from the oceanic ridges (high heat flow and thin seismogenic layer),  $b$ -value variations are small, and all the values are near 1.0.

We also show that the joint interpretation of  $b$ -value and corner magnitude offers a better characterization of the variability in the MFD: while tectonic environments and faulting styles are often correlated, they represent distinct and

interacting factors that influence the distribution of magnitudes. This dual influence is especially evident in geodynamically complex regions such as active continental zones, where mixed kinematics coexist.

## 5.2 Introduction

In Chapter 4, I demonstrated that crustal heat flow explains the first-order global variability of the  $b$ -value. However, heat flow alone cannot capture the full complexity of earthquake size distributions. While it provides information on the thermal regime of the crust, it does not reflect the geometrical and mechanical conditions that control the accumulation and release of elastic strain.

Building on the findings of Chapter 4, this chapter investigates whether tectonic regime and fault kinematics can explain systematic patterns in the MFD beyond those accounted by heat flow. In this sense, the analysis is complementary. Moreover, this chapter extends the previous analysis by explicitly estimating the corner magnitude, a key parameters that characterizes the behavior of the right tail of the MFD. Accounting for this tail is essential, since many observed fluctuations in  $b$ -values may arise from limited constraints on the largest earthquakes or from catalog incompleteness (Chapters 2 and 4, Kagan 1999; 2002; 2003, Marzocchi, *et al.* 2020; Herrmann and Marzocchi 2021; Corrado, *et al.* 2025). To address this, I employ a tapered Gutenberg-Richter, which reduces the biases from the right-hand tail and allows more physically meaningful estimates of  $b$ -values and corner magnitudes.

Previous studies have highlighted the influence of tectonic setting and faulting style on global MFD patterns. Bird and Kagan (2004) show that major tectonic environments exhibit significantly different corner magnitudes, reflecting differences in the occurrence of large events. Kagan *et al.* (2010) further demonstrate that spreading ridges have distinct corner magnitudes and characteristic *b*-values, likely reflecting contrasting tectonic and stress conditions. Faulting style is another important control: normal-faulting earthquakes tend to display higher *b*-values than reverse-faulting events, a pattern linked to stress orientation and fault mechanics (Schorlemmer, *et al.* 2005; Petruccelli, *et al.* 2018, 2019).

In this study, I investigate how both tectonic environments and faulting styles influence the MFD at a global scale, using the up-to-date Global CMT catalog. I first estimate the catalog completeness, accounting for long-term changes in seismic network performance (Ekström, *et al.* 2012) and short-term incompleteness during major sequences (Bird and Kagan 2004; Iwata 2008). Then, I conduct a systematic analysis of global data by grouping events according to tectonic environment and according to faulting style, and I apply statistical tests to assess whether these classifications result in significantly different MFDs.

### 5.3 Data and Methods

#### 5.3.1 Seismic catalog and estimation of the completeness magnitude ( $M_C$ )

We use the same catalog, tectonic zonation and kinematic classification as in Chapter 4.

Again, to guarantee the exponentiality of the magnitude distribution in the catalog, I use the Lilliefors test (Herrmann and Marzocchi 2021).

To check the stability of the results of my analysis, I also explore more conservative scenarios by raising all completeness values by 0.2 and selecting events accordingly.

#### 5.3.2 Estimation of the MFD parameters

In this chapter, I estimate the  $b$ -value using the method proposed by Taroni (2021, see “Estimation of the  $b$ -value”) alongside with the joint estimation of the  $b$ -value and the corner magnitude ( $C_M$ )—the parameters of the tapered Gutenberg–Richter distribution—using the extended maximum-likelihood approach of Taroni *et al.* (2021). In this case, seismic moment must be used instead of  $M_W$  magnitudes. The joint likelihood is computed for all observed seismic moments while accounting for a completeness magnitude that varies with time.

The estimations of the  $b$ -value and the corner magnitude are obtained by maximizing such joint likelihood, and the uncertainties relative to these

parameters are computed using the profile-likelihood method (Taroni, *et al.* 2021; see “Joint estimation of the  $b$ -value and corner magnitude”).

### 5.3.3 Statistical tests to compare MFDs

To assess whether the differences in  $b$ -values are statistically significant, I apply the Utsu test (Utsu 1966).

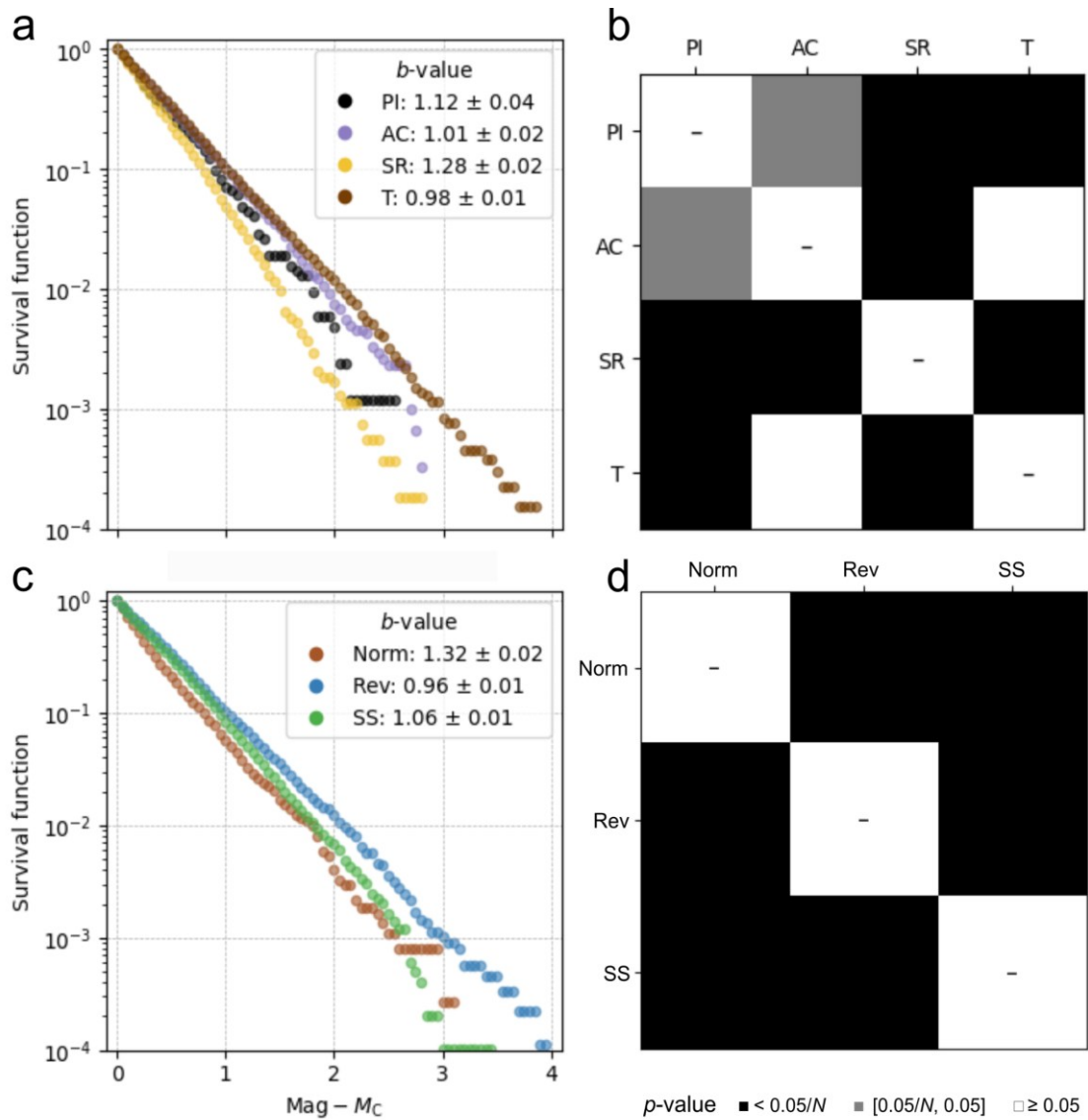
Additionally, to compare the magnitude distributions of the two groups, I employ the two-sample Kolmogorov–Smirnov (KS) test (Gibbons and Chakraborti 2003). For all analyses, I adopt an initial significance threshold of 0.05, and then I correct it to  $0.05/N$ , where  $N$  is the number of tests performed, to consider the multiple testing problem (Bonferroni 1936).

## 5.4 Results

Starting from the two main interpretations of the global variations of the MFDs (see “Introduction”), I divide the earthquake data from the CMT (Dziewonski, *et al.* 1981; Ekström, *et al.* 2012) according solely to the tectonic environment (Bird 2003), and then according only to the fault kinematics (see “Data and Methods”).

Figure 5.1 shows the MFDs and the  $b$ -values of those sub-groups. Figure 5.1a shows that the spreading ridges (yellow) are characterized by the highest  $b$ -value while the trenches (brown) are characterized by the lowest, indicating a relative abundance of smaller events with respect to the larger ones in the spreading ridges and the opposite for trenches. Figure 5.1b shows the results of

the Utsu test (1966) performed by each couple of  $b$ -values previously estimated: black cells indicate which combination of  $b$ -values returns a  $p$ -values of the Utsu test smaller than  $0.05/N$  (see “Data and Methods”), meaning that those  $b$ -values are significantly different at this level. Grey cells indicate the combinations that return a  $p$ -value between  $0.05/N$  and  $0.05$ , and the white ones the combinations that return a  $p$ -value greater than  $0.05$ , hence the  $b$ -values are not statistically different. Some of the subdivisions show significant differences in the  $b$ -values, although the separation is less clear in some regions. Only the geodynamically complex regions such as active continental zones, where mixed kinematics coexist (see Figure 12.1), are less separated from the others.



**Figure 5.1 MFDs and  $p$ -values of the Utsu test between the  $b$ -values.**

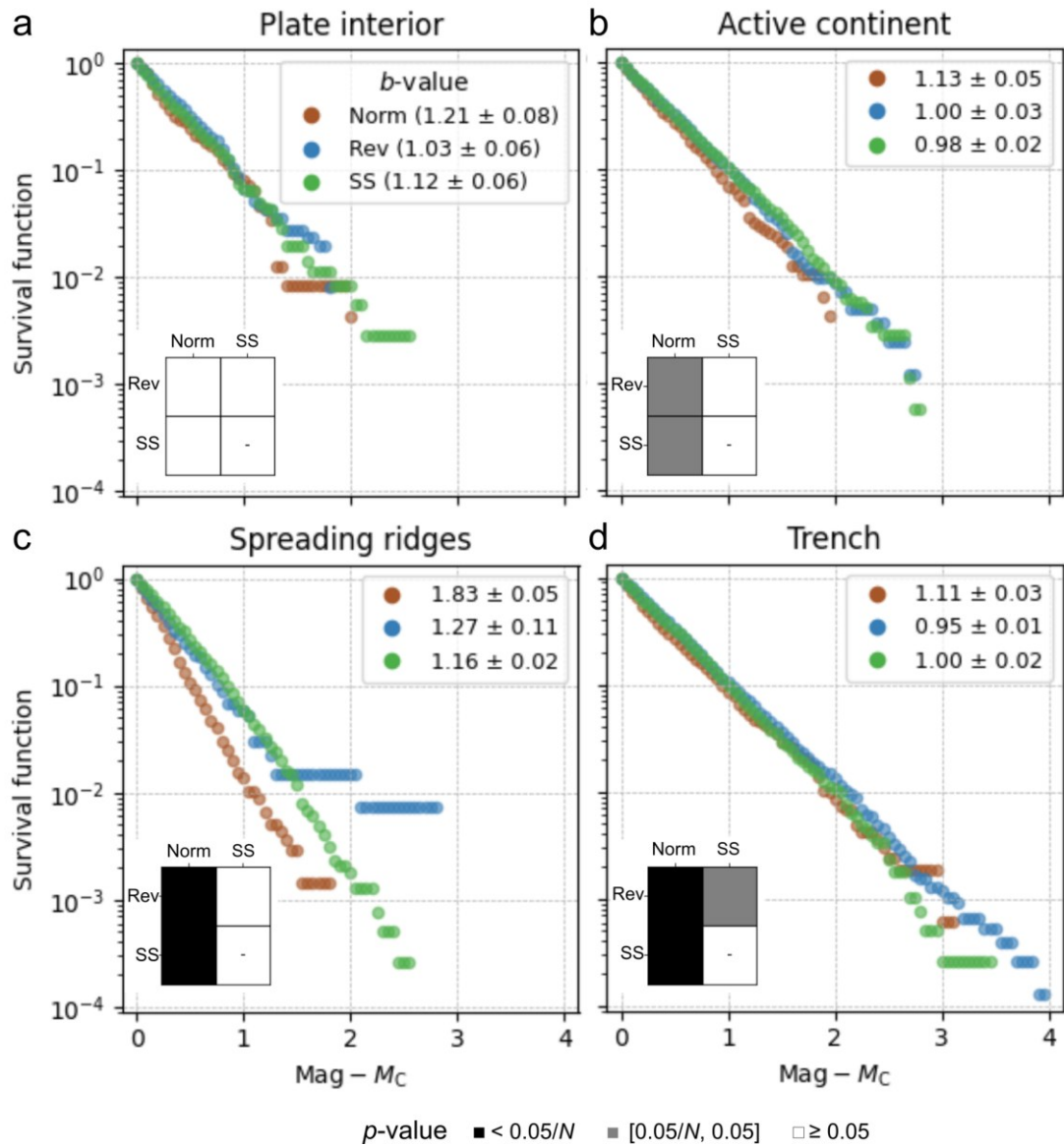
Panels a and b are referred to the events grouped according to the tectonic environment (Bird 2003): PI = plate interior, AC = active continent, SR = spreading ridges, T = trench. Panels c and d refer to the events grouped according to the fault kinematics (see “Data and Methods”): Norm = normal kinematics, Rev = reverse kinematics, SS = strike-slip kinematics. Panels b and d show the results of the Utsu test (1966).

For confirmatory results obtained using the second solution of the CMT see Figure 12.2 and using a more conservative estimation of the  $M_c$  see Figure 12.3 and Figure 12.4.

Similarly, Figure 5.1c and d show the MFDs and the results of the Utsu test, this time grouping the events according to the fault kinematics. In this case, the normal events have the highest  $b$ -values, while the strike-slip the lowest. This confirms what has been shown by Petruccelli *et al.* (2018; 2019). The results of the Utsu test show that all the  $b$ -values are statistically different from each other. These tests can be also interpreted jointly. Indeed, faulting styles are not evenly distributed along the different tectonic environments, with a prevalence of normal and strike-slip faulting in ridges (97.5% of the total), of inverse faulting in trenches (58.0% of the total), and a more variable distribution in active continents and plate interior, which both show intermediate (averaged)  $b$ -value. To better investigate this point, as the different faulting styles can occur even within the same tectonic environment (Figure 12.1), I classified the events first according to the tectonic environment (Bird 2003) and then according to the faulting mechanism, as explained in the “Data and Methods” section, and then I repeated the analysis.

Figure 5.2 shows the MFDs of the events grouped according to the tectonic environment (panels) and then according to the fault kinematics (colors). Notably, within each tectonic environment, the  $b$ -values vary considerably across different faulting styles, indicating that the overall trend in Figure 5.1c averages diverse behaviors with the  $b$ -values of the normal events being always the highest. The other faulting styles are instead more mixed, with the  $b$ -value of strike-slip seismicity being intermediate between normal and reverse faulting

only in active continents and trenches. The statistical tests (inserts in Figure [5.2](#)) show that the equal  $b$ -value hypothesis can be mostly neglected, apart from all comparisons of plate interiors (probably due to the lack of events in this domain, see Figure [4.3a](#)) and the comparison between strike-slip events and reverse events in active continent and spreading ridges. Even when applying a more conservative significance threshold to account for multiple testing, the comparisons between normal and reverse events, as well as between normal and strike-slip events, still reveal significantly different  $b$ -values in both spreading ridges and trenches (black cells).



**Figure 5.2 MFDs for each type of kinematics in each tectonic environment.** Red = normal, blue = reverse, green = strike-slip; plate interior (a), active continent (b), spreading ridges (c) and trench (d) (Bird 2003). The  $b$ -values and the relative uncertainties are listed in each legend. The inserts in each panel indicate the results of the Utsu test between the  $b$ -values listed in the legend (as in Figure 5.1b and d). For confirmatory results based on the second solution of the CMT see Figure 12.5 and using a more conservative estimation of the CMT see Figure 12.6 and Figure 12.7.

I then move my analyses to the tapered Gutenberg–Richter model, which may better capture the behavior of the tails of the magnitude distributions

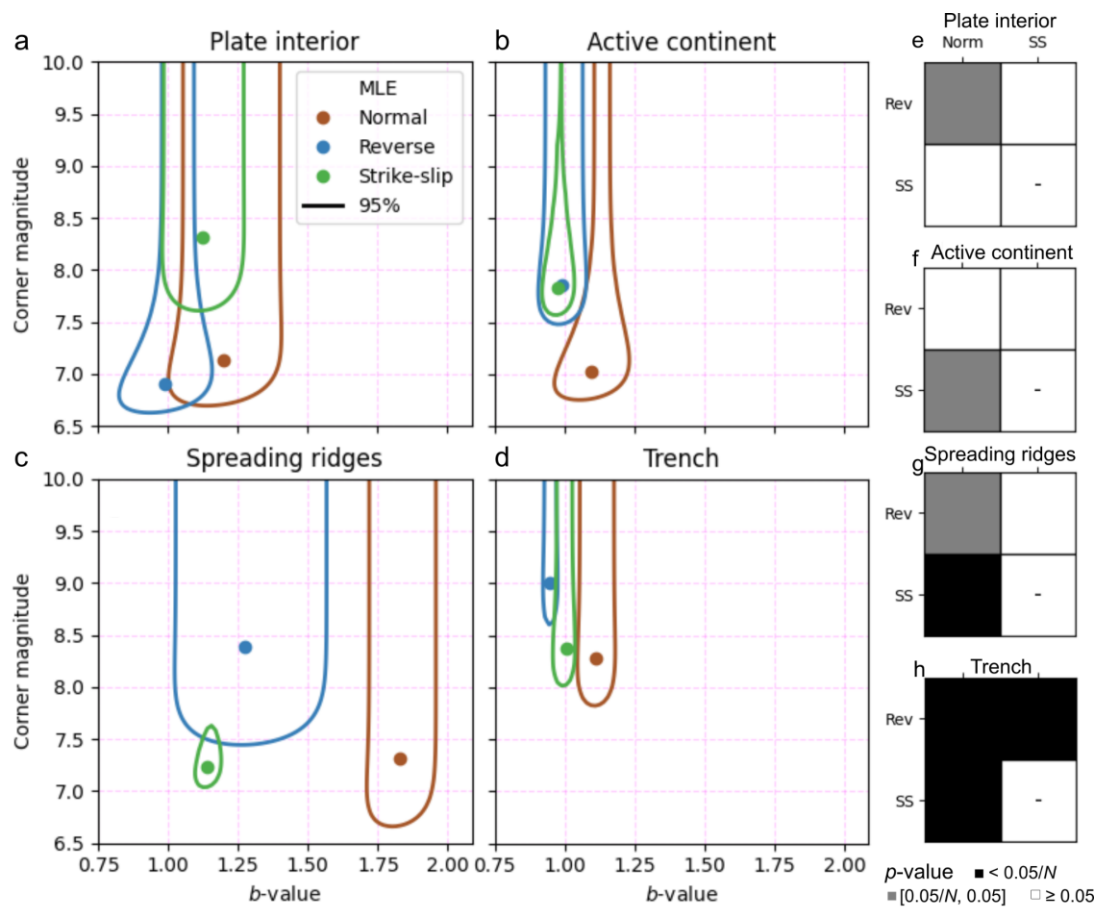
(Taroni, *et al.* 2021). Figure 5.3 shows the estimated  $b$ -values and corner magnitudes ( $C_M$ ) for each combination of tectonic environment and faulting style (see “Data and Methods”). Each panel corresponds to a different tectonic environment, and colored dots represent the estimated parameters for normal (brown), reverse (blue), and strike-slip (green) events. The contours indicate the 95% confidence regions. Within each tectonic environment, the three kinematic styles tend to occupy distinct regions of the parameter space.

For instance, in the plate interior (panel a) each faulting style exhibits a distinctive pair of  $b$ -value and corner magnitude: reverse-faulting events (blue) show the lowest values, strike-slip events the highest corner magnitudes with intermediate  $b$ -values, and normal events occupy an intermediate position. In the active continent domain (panel b), instead, normal events follow entirely different distributions of  $b$ -values and corner magnitudes, while reverse and strike-slip events overlap—both yielding relatively low  $b$ -values but elevated corner magnitudes.

In spreading ridges and trenches, the three main faulting styles exhibit different patterns in  $b$ -values and corner magnitudes. In spreading ridges (panel c), normal events generally have higher  $b$ -values than reverse and strike-slip events, although their corner magnitudes overlap with those of reverse events. Strike-slip events show  $b$ -values like reverse ones but systematically lower corner magnitudes. The 95% confidence intervals for both  $b$ -values and corner magnitudes indicate that these differences are distinguishable within the error

margins. Taken together, these observations suggest that each faulting style occupies a distinct segment of the magnitude-frequency distribution, while acknowledging some overlap. This pattern confirms within statistical uncertainty, the trend observed in the Atlantic ridge by Taroni *et al.* (2021).

Finally, in trenches (panel d) all three kinematic categories cluster around close  $b$ -values and corner magnitudes, but their 95 % confidence intervals remain non-overlapping along the  $b$ -value dimension, confirming statistically distinct distributions for each faulting style.



**Figure 5.3** Maximum likelihood estimations and 95% confidence level of the parameters of the tapered Gutenberg-Richter in different tectonic environments: plate interior (a), active continent (b), spreading ridges (c) and trench (d). Panels e-h) p-values of the two-samples KS test between the magnitude distributions of different fault kinematics within the same tectonic environment. For confirmatory results based on the second solution of the CMT see Figure 12.8 and for confirmatory results based on a more conservative estimation of the  $M_c$  see Figure 12.9 and Figure 12.10.

To test this, I apply the two-sample KS test (Figure 5.3e–h, see “Data and Methods”) to every pair of kinematic styles within each tectonic environment (as in the inserts in Figure 5.2). While this test is less powerful than the Utsu test, it can reveal differences not only in  $b$ -values but also in corner magnitudes. In plate interiors (Figure 5.3e), the KS test returns a  $p$ -value of 0.02 for the

comparison between normal and reverse events, indicating a difference in their magnitude distributions, whereas the Utsu test does not detect this difference (see Figure 5.2a). In other environments,  $p$ -values for most comparisons exceed 0.05, suggesting no statistically significant differences. These results indicate that some differences between magnitude distributions are statistically significant, primarily in the slope and corner magnitudes, as also suggested by the patterns visible in Figure 5.3a.

In the active continents (Figure 5.3f) the magnitude distributions of normal and strike-slip events are significantly different, being characterized by similar  $b$ -values but very different corner magnitudes.

Instead, in spreading ridges (Figure 5.3g) the results of the KS test confirm the ones of the Utsu test but considering the multiple testing the difference between normal and reverse events is not significant anymore, probably due to the relative lack of the latter in that tectonic environment (only 2.5% of events have a reverse kinematics).

Also, in trenches (Figure 5.3h) the KS test returns similar results to the Utsu test, but even considering the multiple testing, the difference between reverse and strike-slip events is significant, behind the two distributions characterized by different and non-overlapping intervals of  $b$ -value and corner magnitude.

Overall, these results suggest that the MFD shapes vary systematically with both tectonic environment and faulting style.

## 5.5 Discussion and conclusions

The observed separations on MFD demonstrate that different faulting styles have distinct seismic potential, even under the same tectonic regime. This implies that both tectonic environment and faulting style significantly and independently influence the shape of the MFDs, as reflected in systematic variations of the  $b$ -value and corner magnitude. In the future, we aim to investigate which of these two factors exerts a stronger influence on the MFD characteristics.

While previous global-scale studies (e.g., Bird and Kagan 2004; Kagan, *et al.* 2010) emphasized that broad tectonic regimes control the upper limit of earthquake sizes, my results suggest that the observed differences in MFDs among tectonic environments may primarily reflect variations in the mechanical properties of the crust, such as medium strength and rheology, which tend to correlate with tectonic setting, rather than the tectonic regime itself directly controlling earthquake magnitudes. Within this context, the kinematic style of individual faults provides an additional layer of control, modulating both the relative abundance of smaller events and the frequency of larger ones.

Spreading ridges, where tectonics is mostly extensional (see Figure [12.1](#)), relatively host a big portion of the normal-faulting earthquakes and exhibit high  $b$ -values and low  $C_{MS}$ , reflecting many small to moderate events and an earlier tapering of the largest magnitudes. Moreover, even within compressional trench

settings, the subset of normal-faulting events still shows systematically higher  $b$ -values and lower  $C_{MS}$  than reverse-faulting events. This indicates that the kinematic style imposes its own statistical signature on the MFD regardless of the main tectonic regime. However, the same faulting style in different tectonic environments shows very different MFDs.

Petrucelli *et al.* (2018; 2019) specifically observed a global  $b$ -value peak for normal-faulting events, which mixes a global trend of larger  $b$ -values in normal faulting, but averages over very different situations in the different tectonic regimes. Large  $b$ -values are indeed observed for all faulting styles in ridges. As normal-fault earthquakes are disproportionately concentrated along spreading ridges, this amplifies the effect, mixing two different controls. Similar considerations may be made about the other faulting styles. While the global scaling (Kagan, *et al.* 2010) remains a reliable baseline for average behavior in each tectonic environment, my analysis underscores that the local faulting style modulates both the relative abundance of smaller events and the frequency of the larger magnitudes. This dual control is especially critical in geodynamically complex regions—such as active continental zones—where multiple faulting regimes coexist (Figure [12.1](#)).

Notably, many of the differences in MFDs can be fully appreciated only by observing jointly  $b$ -values and corner-magnitudes, like in the case of active continent, where significant correlations exist among the parameters, making

the marginal distributions of  $b$ -value and corner magnitudes similar, but overall joint distributions well separated.

However, apart from the spreading ridges, the differences between the  $b$ -values, although statistically significant, are smaller with respect to previous studies (Schorlemmer, *et al.* 2005; Petruccelli, *et al.* 2018; 2019). Outside the spreading ridges, most of the estimated  $b$ -values spread between 0.95-1.13, i.e. near 1.0: such a limited range of variability has important implications in seismic hazard studies, and confirms the results obtained for regional catalogs by Taroni and Carafa (2023).

This reasoning could be extended beyond the global and regional scale. In principle, the same dual control exerted by tectonic environment and faulting style could also operate at smaller, more local scales. Individual fault systems, or even single major structures, may display systematic differences in their MFDs according to their kinematics. For example, normal, reverse, or strike-slip segments within the same seismotectonic zone could still exhibit distinct combinations of  $b$ -values and corner magnitudes, reflecting how local geometry and stress regime condition the frequency of small events and the occurrence of large ones. This perspective suggests that fault-specific MFD characterization may provide additional insights for seismic hazard assessments at local scale, where the relative contribution of different kinematic styles becomes particularly relevant.



# 6

## MAGNITUDE-DEPENDENT FOCAL MECHANISM FORECAST

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I contributed to the conceptualization of the study, curated and analyzed the data, carried out the investigation, developed methodology and software, created visualizations, and co-wrote both the original draft and the review/editing of the manuscript.

## 6.1 Abstract

Reliable forecasts of earthquake focal mechanisms are essential for probabilistic seismic and tsunami hazard assessments. Traditional averaging-based methods provide useful estimates but often obscure their natural variability, especially in geodynamically-complex or data-poor regions. Here I present a Bayesian framework for forecasting focal mechanisms that combines physically constrained discrete priors with observational data from earthquake catalogs and geological information from fault inventories. Using the Global CMT catalog and the Mediterranean region as case study, I demonstrate that focal mechanism distributions strongly vary with both tectonic setting and the magnitude range, this should be considered to produce unbiased forecasts. Application to the Mediterranean region reveals that forecasts based on all magnitudes are dominated by smaller events, while restricting the analysis to larger magnitudes enhances the prevalence of reverse faulting and reduces spurious extension or strike-slip contributions. Comparisons using the Kagan angle confirm that differences between magnitude-conditioned models and all-magnitude models are largest in areas with active faults and large events. The framework, and its corresponding Python code, is modular and adaptable to different regions and datasets, offering a reproducible methodology for constructing spatially resolved, magnitude- and/or tectonic-dependent forecasts of focal mechanisms.

## 6.2 Introduction

Chapters 4 and 5 demonstrate that the magnitude distribution is not universal, but it depends significantly on the tectonic environment, the fault kinematics and the heat flow. This chapter tries to integrate that information in a practical field: the forecast of focal mechanism.

Reliable forecasts of earthquake focal mechanisms—the orientation and slip direction of faulting—are fundamental to both probabilistic seismic hazard analysis (PSHA) and probabilistic tsunami hazard analysis (PTHA). Traditional approaches (Kagan and Jackson 2014; Roselli, *et al.* 2018, Selva and Marzocchi 2004), typically rely on the Kostrov method (Kostrov 1974), which estimates the most likely focal mechanism at a given location by averaging nearby seismic moment tensors, with weights based on event magnitude and distance. While effective in data-rich regions, this averaging can mask some variability in the underlying distributions.

As an alternative to averaging-based approaches, Selva *et al.* (2016) propose a probabilistic model in which, in each target area, all potential geometries and faulting mechanisms simultaneously are explicitly forecasted. This means that, instead of producing an average, a probability is assigned to each possible focal mechanism, describing the full range of potential variability of focal mechanisms in each target area. In Selva *et al.* (2016), the seismogenic domain is divided into tectonically homogeneous regions, and the possible physically plausible combinations of angles are discretized into intervals. All these

intervals were initially assumed equally probable. The resulting prior is semi-informative as probabilities are uniformly assigned to all admissible bins. This prior was subsequently updated with observations in large tectonic regions with a Dirichlet/Multinomial Bayesian scheme, to produce a regional posterior. This posterior was taken as prior in local environments, to be updated with further local information, like for example known faults.

Other works explore different approaches, with a stronger focus on the rake angle: Roselli *et al.* (2017) introduced a forecasting model based on a weighted summation of past focal mechanisms over a regular grid, providing for each cell the expected probability of normal, reverse, or strike-slip faulting. Pondrelli *et al.* (2002) extend this perspective by defining the style of faulting combining focal mechanisms with geological and seismotectonic constraints. Their method allows to capture lateral and vertical variability in faulting style, providing robust estimates where sufficient data exist, while resorting to random or mixed styles where information is limited.

Building on the same methodological framework, Taroni and Selva (2021) update this method to allow for global applicability. This approach uses a prior informed by Anderson's theory to model the correlation between rake and dip and optimizes this prior through a "blind" application on global data (Huc and Main 2003). The resulting optimized prior is then locally updated with observed focal mechanisms via Dirichlet-Multinomial Bayesian scheme, thus adapting the prior to local characteristics.

In this work, I first investigate the global seismicity to investigate if not only the tectonic setting, but also the magnitude of target events may control the inferred focal mechanism distribution. To this end, I analyze the global CMT catalog (Dziewonski, *et al.* 1981; Ekström, *et al.* 2012), classifying events by tectonic setting according to Bird (2003).

As my analysis reveals that the spatial distribution of rake and dip angles is not uniform and depends both on the tectonic environment and on the magnitude range considered, the inclusion of this information may eliminate a bias in forecasting focal mechanisms. Then, I develop a code implementing the Bayesian framework described above, based on the Dirichlet-Multinomial conjugacy. The code allows to update an a-priori distribution of focal-mechanism parameters for each region of a predefined regionalization (which may also be a grid). The user may choose between setting this prior as semi-informative (as in Selva, *et al.* 2016), or on Anderson's theory (as in Taroni and Selva 2021), or on any other distribution defined by the user. The prior is then combined with two potential sources of new information: (i) observed focal-mechanism solutions from the earthquake catalog, and (ii) fault-specific contributions based on geological data and slip rates. Magnitudes may not be filtered, as in Selva *et al.* (2016) and Taroni and Selva (2021) or may be filtered based on the target magnitude range for the inference. The resulting posterior distribution integrates these observational and geological constraints, providing an updated, spatially resolved probability model of focal mechanisms.

### 6.3 Analysis of magnitude dependence on focal mechanism distribution

While other models primarily emphasize tectonic setting as the key driver of focal mechanism variability, my analysis suggests that the focal mechanism distribution is different for different magnitude ranges. To explore this possibility, I examine the global CMT catalog (Dziewonski, *et al.* 1981; Ekström, *et al.* 2012), focusing on how rake and dip distributions change across both tectonic environments and magnitude ranges.

Figure [6.1](#) illustrates these variations, considering all the events together (panel a) and then dividing them by the tectonic environments in which they occur (panels b-e), highlighting the interplay between tectonic context and magnitude.

In the GCMT dataset (Figure [6.1a](#)), the rake distribution is dominated by reverse faulting. By contrast, the peaks associated with normal and strike-slip mechanisms are primarily expressed at lower magnitudes, and their relative importance diminishes as magnitude grows. The dip distribution is broad, but low-magnitude events tend to cluster at intermediate dip values, whereas larger earthquakes are more uniformly distributed and show a slight preference for steeper dips.

In plate interiors (Figure [6.1b](#)), the rake distribution at low magnitudes exhibits two prominent peaks corresponding to normal and reverse faulting, alongside a smaller strike-slip peak. As the magnitude increases, the reverse and strike-slip contributions decrease, shifting the balance in favor of normal faulting.

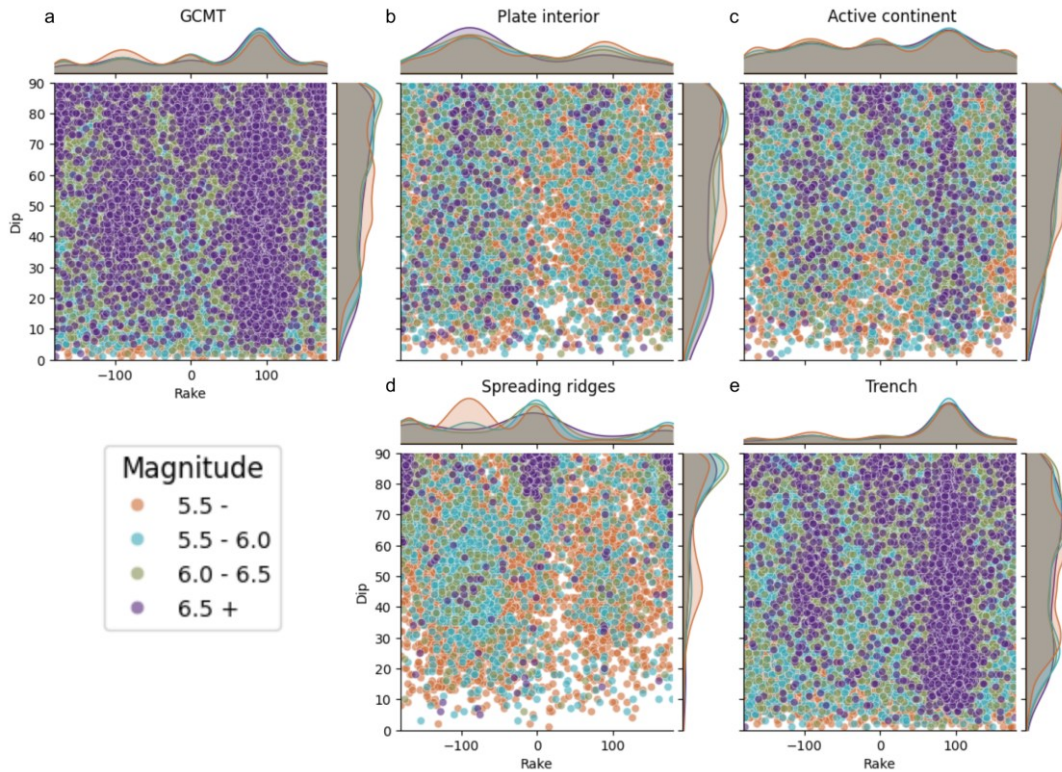
Active continental regions (Figure 6.1c) exhibit a similar but more gradual transition: at low magnitudes, strike-slip, normal, and reverse faulting modes are all present, whereas at higher magnitudes the modal structure becomes less distinct and reverse faulting gains relative prominence. This pattern may indicate that, although regional boundary stresses are relatively uniform, local stresses orientations can vary substantially, influencing the style of large earthquakes and the overall tectonic pattern.

In spreading ridges (Figure 6.1d), the dependence on magnitude is the most pronounced: below approximately magnitude 6, the area is dominated by normal faulting with a noticeable strike-slip component, but at larger magnitudes, the normal faulting signal weakens substantially.

By contrast, subduction trenches (Figure 6.1e) demonstrate comparatively stable behavior, with the relative proportions of thrust, normal, and strike-slip faulting varying little across the tested magnitude bins, resulting in a rake distribution that remains broadly invariant with increasing magnitude.

Dip-angle behavior reinforces this picture. In plate interiors, small events concentrate around  $\sim 50^\circ$ , whereas larger events become bimodal with peaks near  $\sim 20^\circ$  and  $\sim 80^\circ$ . Active continental zones shift from  $\sim 50^\circ$  at low magnitudes to a strong clustering near  $\sim 85^\circ$  at high magnitudes. Ridges show two low-magnitude peaks ( $\sim 85^\circ$  and  $\sim 50^\circ$ ) but lose the  $50^\circ$  mode at higher magnitudes.

In trenches small events populate dips near  $\sim 85^\circ$ ,  $\sim 60^\circ$  and  $\sim 30^\circ$ , yet the  $\sim 60^\circ$  peak fades with increasing magnitude and the dip distribution smooths out.



**Figure 6.1 Rake and dip angle distribution according to the tectonic environment with marginal histograms.**

The data are grouped by magnitude range:  $\leq 5.5$  (orange), 5.5-6.0 (blue), 6.0-6.5 (green) and  $\geq 6.5$  (purple). Rake and dip values of the two solutions of the CMT (Dziewonski, et al. 1981; Ekström, et al. 2012) are combined.

Figure 13.1 gives an alternative vision of that dependence: the radius corresponds to the dip angle, while the circumference represents the rake angles.

At the global scale (panels a–c), increasing magnitude reduces the occurrence of normal-faulting events.

In plate interiors (d–f), larger magnitudes are associated with fewer reverse-faulting events, while high-angle normal events become more common (at the expense of low-angle ones).

In active continental regions (g–i), the proportion of normal events decreases, whereas reverse events increase in dip angle.

At spreading ridges (j–l), normal events vanish as magnitude increases, leaving only strike-slip faulting.

In trenches (m–o), reverse events consistently occur at both low and high dip angles, regardless of magnitude.

### 6.4 Code for focal mechanism forecast

The purpose of this work is to provide a reproducible procedure to construct forecasts of the focal mechanisms, based on:

- a discrete prior on focal mechanisms (strike, dip, rake);
- a catalog of moment tensors including the two possible nodal plane solutions for each event;
- an inventory of faults;
- a map of tectonic regions;
- the target magnitude for the forecast.

The approach follows a discrete Dirichlet/Multinomial Bayesian formulation (as proposed in Selva, *et al.* 2016), combining a Dirichlet prior with observational multinomial counts to obtain a Dirichlet posterior distribution.

The discretization of focal mechanisms is performed as in Selva *et al.* (2016), with 144 discrete bins covering all possible focal mechanisms.

### 6.4.1 Data and pre-processing

The minimum required information for the event catalog are longitude, latitude, strike1, dip1, rake1, strike2, dip2, rake2, moment magnitude, and depth. During processing, events are optionally filtered based on depth, retaining only those shallower than a predefined maximum depth, and optionally based on a magnitude range, if specified.

The input for tectonic regions is a text file containing polygons. Under request, a regular square cell of the desired side  $L$  (in my case of 25 km) are constructed using a local equirectangular projection, where the reference latitude is taken as the average latitude of the region. Coordinates are converted according to

$$x = R \cos(\varphi_0) \Delta\lambda, y = R \Delta\varphi, \quad (6.1)$$

where  $R = 6371$  km and  $\Delta\lambda$  and  $\Delta\varphi$  are expressed in radians.

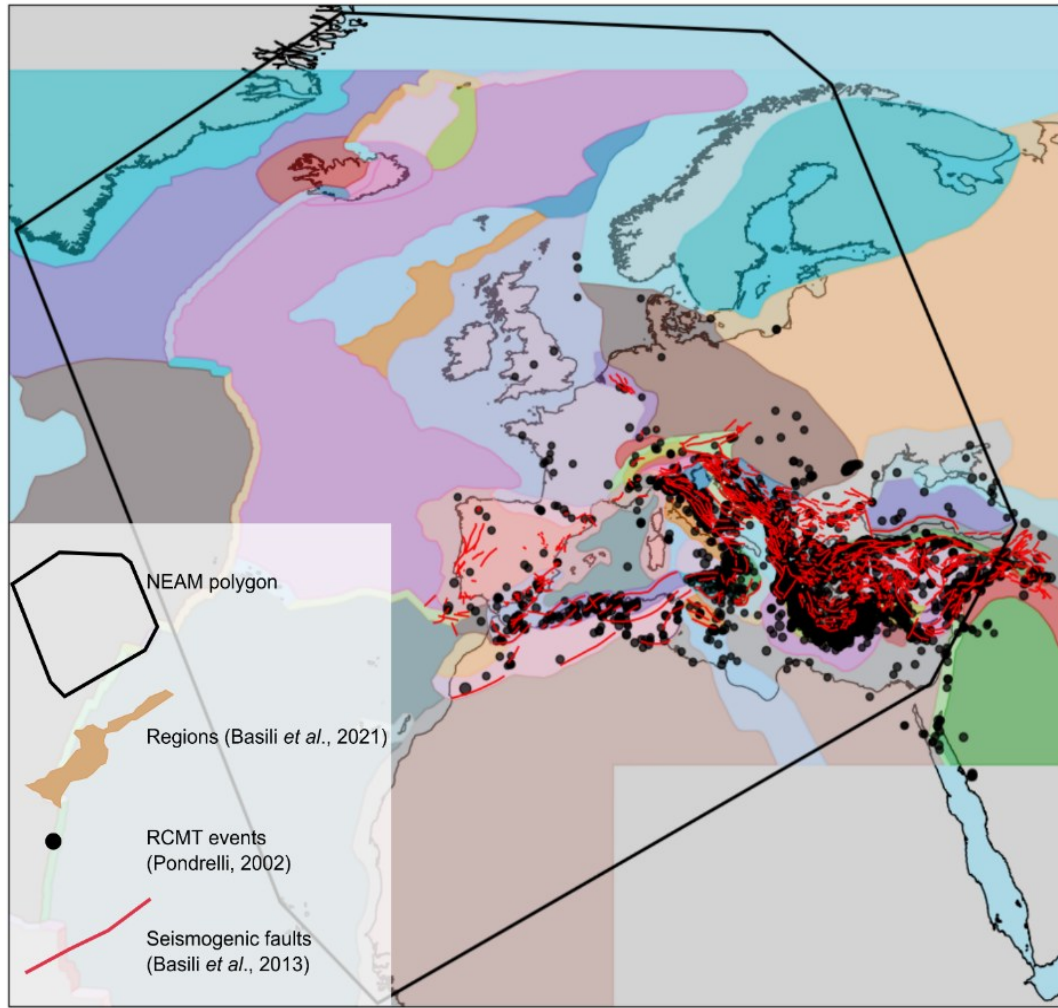
The input for the fault inventory consists of a shapefile containing the planes of the faults. From the shapefile, the following information is extracted, when available: strike, dip, and rake (averaged between minimum and maximum values), moment rate, as well as minimum and maximum depth.

The modeling framework is fully customizable with respect to the input datasets: users can upload catalogs, tectonic regionalization, fault inventories, grid resolutions, magnitude ranges, and depth filters according to the needs of

their specific study area. For the purpose of this work, I focus on the Mediterranean region and adopt datasets that offer the best balance between homogeneity, completeness and regional consistency.

Specifically, I use the Mediterranean Regional Centroid-Moment Tensors Catalog (RCMT, Pondrelli 2002) for seismic events, the regionalization from the TSUMAPS-NEAM project for tectonic regions (Basili, *et al.* 2021), and the European database of seismogenic faults as the fault inventory (Basili, *et al.* 2013). However, the code and methodology are general and can be adapted straightforwardly to other regions worldwide by substituting these inputs with appropriate local or global datasets.

Figure [6.2](#) shows the databases that I use for the analysis.



**Figure 6.2** Map of the study region (NEAM area) with overlaid seismic events and seismogenic faults.

Colored areas indicate the different geological regions defined by Basili et al. (2021). Black circles mark the locations of earthquakes (Pondrelli 2002), with sizes proportional to their magnitudes. Red lines represent faults (Basili, et al., 2013) and the black polygon.

#### 6.4.2 Prior distribution and focal mechanism

##### 6.4.2.1 Angle discretization

Strike angles are defined as  $S = \{22.5^\circ, 66.5^\circ, 112.5^\circ, 157.5^\circ\}$  covering the range  $0-180^\circ$ .

Dip angles are taken as  $D = \{10^\circ, 30^\circ, 50^\circ, 70^\circ, 90^\circ, 110^\circ, 130^\circ, 150^\circ, 170^\circ\}$ , and

rake angles as  $R = \{-90^\circ, 0^\circ, 90^\circ, 180^\circ\}$ , where the value  $180^\circ$  represents  $\pm 180^\circ$ . The total number of theoretical combinations is 144, which define the discrete indexed bins (Selva, *et al.* 2016).

Not all combinations are physically admissible. The rules implemented in the code are as follows (Selva, *et al.* 2016):

- For  $r = -90^\circ$  (normal fault), dips  $d \in \{10^\circ, 90^\circ, 170^\circ\}$  are excluded.
- For  $r \in \{0^\circ, 180^\circ\}$  (strike-slip), dips  $d \in \{10^\circ, 30^\circ, 50^\circ, 130^\circ, 150^\circ, 170^\circ\}$  are excluded.
- For  $r = 90^\circ$  (reverse fault), dips  $d \in \{70^\circ, 90^\circ, 110^\circ\}$  are excluded.

This constraint could be removed if such combinations are considered to be reliable (Huc and Main 2003).

#### 6.4.2.2 *Pseudocount prior and normalization*

A prior weight  $w_k$  is assigned to each bin  $(s, d, r)$ : 1 if the combination is allowed, 0 if the combination is excluded (see “Angle discretization”).

The normalized prior probability is then computed as:

$$p_k^{(0)} = \frac{w_k}{\sum_j w_j} \quad (6.2)$$

#### 6.4.2.3 *Contribution of faults*

If faults are available for a cell, their contribution can be included as follows:

- select all faults intersecting a cell;

- define a total fault weight  $W_F$  (we use 100), representing the additional weight to be assigned to the faults relative to the observed counts;
- assign individual fault weights proportional to their moment rate  $M_{0,i}$  in which more events are expected:

$$w_i = \frac{M_{0,i}}{\sum_{j=1}^n M_{0,j}} W_F \quad (6.3)$$

If all  $M_{0,j} = 0$ , I assign weights  $w_i = W_F/n$ .

The weights  $w_i$  assigned to each fault are proportional to their moment rate  $M_{0,i}$ , reflecting the empirical observation that faults with higher moment rates are expected to produce more events. This approach follows the rationale of Kagan (2002): the probability that a future earthquake occurs on a given fault scales with its moment rate. If all faults have zero moment rate, weights are assigned uniformly. This is an empirical choice for distributing expected events and does not imply a causal influence of magnitude on focal mechanism or vice versa.

### 6.4.3 Likelihood and posterior

#### 6.4.3.1 *Normalization and mapping of a nodal plane to discrete bins*

Each seismic event in the seismic catalog has two nodal plane solutions. Before these planes can be compared with the discrete prior distribution (the 144 bins), the angles should be normalized and assigned to a bin (Selva and Marzocchi 2004). This step is necessary because nodal planes have

a symmetry: a plane and its orthogonal counterpart are equivalent and equiprobable representations of the moment tensor, meaning the same event can be described in two ways. Also, the discrete bins of the prior have predefined centers (see “[Angle discretization](#)”). Each plane has to be mapped to the nearest bin while respecting the physical exclusion rules (some combinations are impossible, see “[Angle discretization](#)”)

After normalization, each nodal plane is assigned to the nearest discrete bin in the prior  $(s_c, d_c, r_c)$ . The distances between the plane and each bin are calculated for each angle:

$$\Delta_s = |s - s_c| \quad (6.4)$$

$$\Delta_d = |d - d_c| \quad (6.5)$$

$$\Delta_r = \min(|r - r_c|, 360 - |r - r_c|) \quad (6.6)$$

If the selected bin is excluded in the prior, then the plane is discarded to avoid mapping impossible configurations.

#### 6.4.3.2 *Event counts*

For each event, both nodal plane solutions (plane1 and plane2) are considered with equal weight. In this way, I account for the uncertainty on the real fault plane. To do that, I add 0.5 to the count of the corresponding bin for each plane, if mappable.

Here, I consider events shallower than 30 km (as in Selva *et al.* 2016) and with a magnitude inside a certain range ( $M5.5-$ ,  $M5.5-6.5$ ,  $M6.5+$ ) to assure enough events for the counts.

#### 6.4.3.3 Construction of the posterior

For each region or cell, a vector of pseudo-counts  $\alpha=(\alpha_1,\dots,\alpha_{144})$  is constructed as:

$$\alpha_k = w_k + f_k + c_k \quad (6.7)$$

Where  $w_k$  is the prior pseudocount (see “Pseudocount prior and normalization”),  $f_k$  is the contribution from the fault inventory for the cell, and  $c_k$  is the count from the event catalog (sum of 0.5 per plane). This formulation results in a Dirichlet distribution with parameters  $\alpha$ .

The Bayesian estimate of the posterior mean for the probability of a bin  $k$  is

$$\hat{p}_k = E[p_k | data] = \frac{\alpha_k}{\alpha_0} \quad (6.8)$$

and the variance is

$$Var(p_k) = \frac{\alpha_k(\alpha_0 - \alpha_k)}{\alpha_0^2(\alpha_0 - 1)} \quad (6.9)$$

#### 6.4.4 Evaluating the contribution of the magnitude

To evaluate the contribution of the magnitude range to consider to build the posterior probability distribution (see “Likelihood and posterior”), I use two methods: the Kagan angle and the marginal probabilities.

For each grid cell, I use the probabilities over the 144 bins to compute a probability-weighted average moment tensor (Aki and Richards 2002).

$$\underline{M} = \sum_{j=1}^{144} p_j M(s_j, d_j, r_j) \quad (6.10)$$

where  $p_j$  is the probability of bin  $j$ , and  $M(s_j, d_j, r_j)$  is the unit moment tensor derived from strike, dip and rake, and assuming a scalar moment  $M_0 = 1$ .

The Kagan angle (Kagan 1991) measures the minimum rotation needed to transform one mechanism into another. It is defined as:

$$\theta = \arccos(|\langle \hat{M}_A, \hat{M}_B \rangle|), \hat{M} = \frac{M}{||M||} \quad (6.11)$$

This means that the smaller the angle is, the smaller the difference between the two distributions.

The 144 bins can also be grouped into three faulting styles based on the rake:

- normal (N) for rake between  $-135^\circ$  and  $-45^\circ$ ;
- reverse (R) for rake between  $45^\circ$  and  $135^\circ$ ;
- strike-slip (SS) otherwise.

By computing the marginal probabilities on normal, reverse and strike-slip mechanisms between the two distributions, I can assess whether the relative balance of faulting styles changes. A large difference indicates a shift in the relative contribution of the three styles.

## 6.5 Results for the Mediterranean area

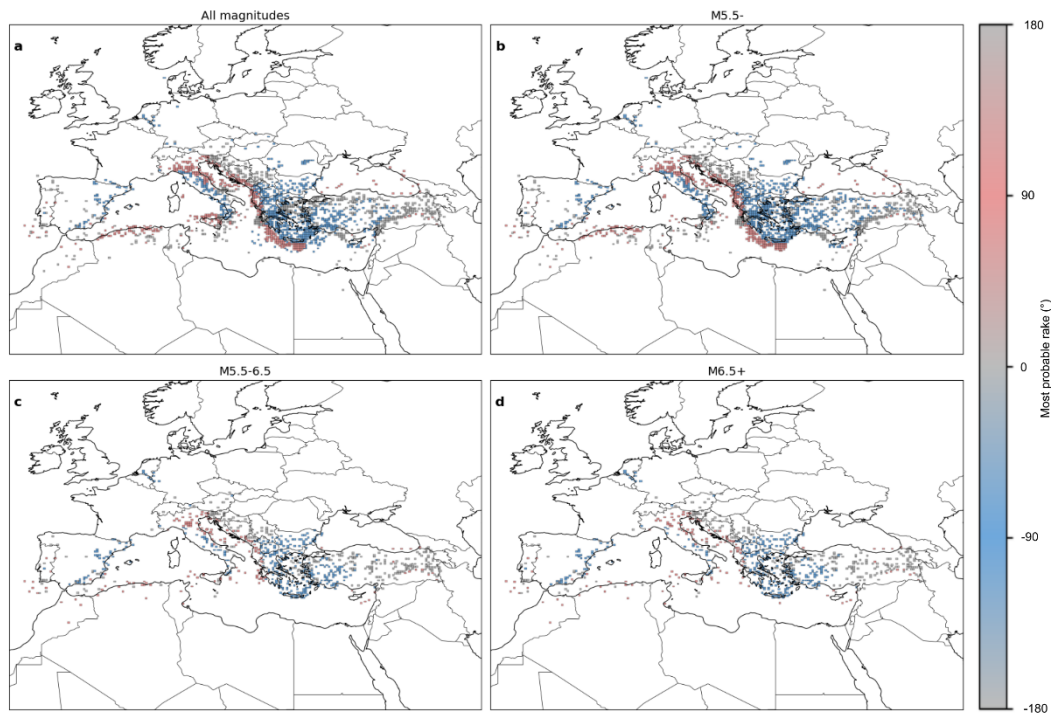
We observe that rake and dip angles systematically vary with earthquake magnitude, with distinct patterns emerging across different tectonic environments (“Analysis of magnitude dependence on focal mechanism distribution” and Figure 6.1). Since these magnitude-dependent variations are robust, they can be treated as valuable information to improve the forecasting of focal mechanisms, rather than relying solely on tectonic settings. I now consider applying the methods described above to the Mediterranean area.

### 6.5.1 Focal mechanism probability distribution for the Mediterranean area

Since I have shown that magnitude influences the distribution of focal mechanisms (“Analysis of magnitude dependence on focal mechanism distribution”), this observation can be exploited as additional information. By incorporating it into the Bayesian framework, I can obtain a posterior distribution that better reflects the actual variability of focal mechanisms, rather than relying only on a global or regime-specific region (“Code for focal mechanism forecast”).

The area that I chose for the application of the forecasting model is the one used by the TSUMAPS-NEAM project (Figure 6.2, black polygon) for the easy availability of geological and seismic datasets. Therefore, from now on I consider only the regions, earthquakes and faults inside that polygon.

Figure 6.3 illustrates how the spatial distribution of the most probable rake (the mode of the marginal distribution) changes depending on the magnitude range considered with colors indicating reverse (red), normal (blue), and strike-slip (grey) mechanisms.



**Figure 6.3** Most probable rake according to the posterior probability distribution built using different magnitude thresholds.

All magnitudes (a), only magnitudes smaller than 5.5 (b), between 5.5 and 6.5 (c) and larger than 6.5 (d) in the RCMT (Pondrelli 2002).

When considering all magnitudes (panel a), reverse mechanisms are mainly concentrated in along the northern African margin, at the frontal sector of the Apennines, in the southern part of Dinarides, in Eastern Anatolia, in the Caucasus, and in the Ionian part of Calabria. For lower magnitudes (panel b), the same general pattern is preserved, but with a marked concentration in the southern portion of the Hellenic Arc. At intermediate magnitudes (panel c), this

concentration in the Hellenic Arc disappears, while clusters remain in the Apennine front, Albania, the Caucasus, Eastern Anatolia, and North Africa. A similar distribution is also observed for the largest events (panel d).

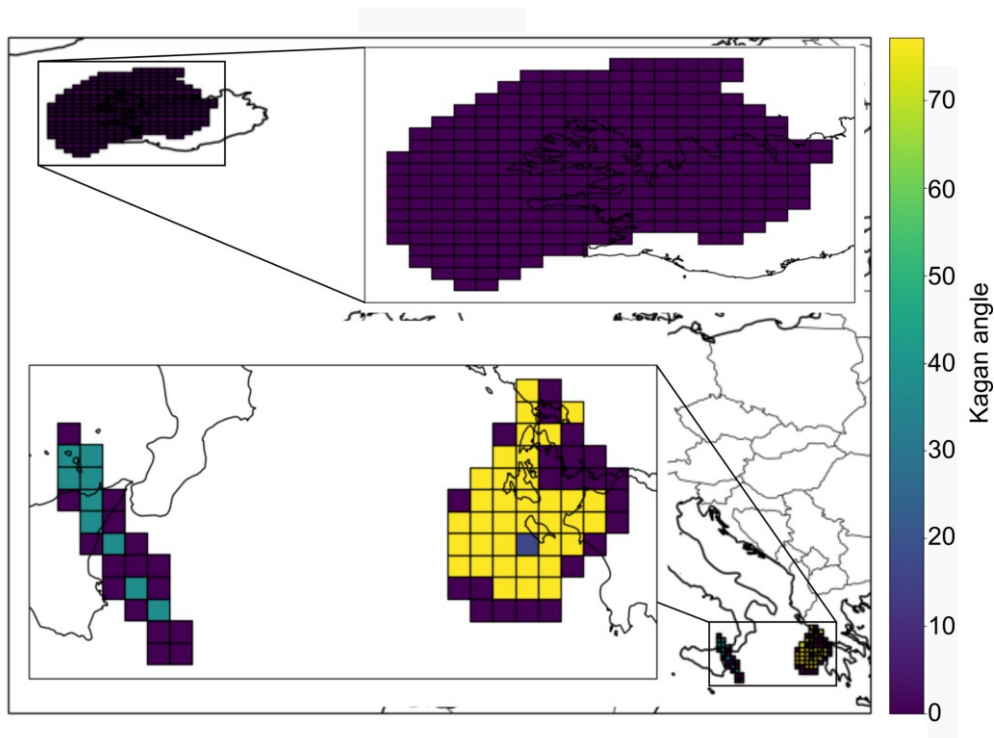
Instead, for normal mechanisms, when considering all magnitudes, they are mainly concentrated in the Apennines and the Calabrian–Tyrrhenian Arc, in the Pyrenees, in the Betics, and across most of Aegean-Anatolian region. For lower magnitudes, the same distribution is observed. At intermediate and higher magnitudes, their overall concentration decreases, although the spatial distribution remains essentially unchanged.

Finally, when considering all magnitudes, strike-slip mechanisms are mainly concentrated in the Dinarides, Betics, in the Ionian sector of Calabria, and in Turkey. For lower magnitudes, the same pattern is observed. At intermediate and higher magnitudes, however, the cluster in the Calabrian area disappears, while the other concentrations remain.

Quantitatively, when considering all magnitudes (panel a), normal faulting is the most common mechanism, present in 40.8% of the cells, followed by strike-slip (35.8%) and reverse faulting (23.4%). For smaller magnitudes ( $M < 5.5$ , panel b), normal faulting remains dominant in 46.1% of the cells, with strike-slip and reverse faulting occurring in 30.8% and 23.1% of the cells, respectively. For intermediate magnitudes ( $5.5 \leq M < 6.5$ , panel c), normal faulting again predominates (43.1%), while strike-slip and reverse mechanisms are observed in 38.4% and 18.5% of the cells. Finally, for the largest magnitudes ( $M \geq 6.5$ ,

panel d), normal faulting is present in 43.5% of the cells, strike-slip in 38.7%, and reverse faulting in 17.8%.

To quantify the overall difference between the distributions considering or not considering magnitude, I computed the Kagan angle (Kagan 1991) for each cell, comparing the probability-weighted average moment tensors obtained from all events and from events with  $M \geq 6.5$ . Figure 6.4 shows the resulting map of Kagan angles for three representative regions (Kefalonia Lefkada, Alfeo-Eolie, Western Atlantic). I choose these regions to show the influence of the (non-)occurrence of events and faults in the probability distributions.



**Figure 6.4** Map of the Kagan angle for representative regions between the probability distribution built considering all the magnitudes and only magnitudes larger than 6.5.

For comparative results with  $M5.5$ - and  $M5.5-6.5$  see supplementary Figure 13.4.

This map shows that in a region where there are no seismogenic faults or where there are no events with magnitude larger than 6.5 (Western Atlantic), the Kagan angle is identically 0. This means that the two distributions are essentially the same due to an essential lack of observation and, in this case, they are the same as the prior distribution.

Instead, in regions characterized by seismogenic faults and where big events occurred, (insert in Figure 6.4), the map of the Kagan angle shows where additional information has influenced the posterior distribution. The two regions are indeed influenced by either the presence of faults and/or large events (see Figure 6.2), which have a prevalent focal mechanism which does not correspond to the most common focal mechanisms of the smaller seismicity. For example, in the Kefalonia Lefkada area there are many surficial strike-slip events along with reverse subduction events on the Hellenic subduction. This is tracked by the magnitude filter, which is in fact characterized by higher Kagan angles and therefore more different forecast distributions for large magnitude events.

### 6.6 Discussion and conclusions

Our analysis demonstrates that the distribution of focal mechanisms varies not only with the tectonic environment but also strongly depends on the magnitude range of the events considered. This magnitude dependence is clearly reflected in the global CMT catalog, which shows that the distribution of rake and dip angles significantly vary with magnitude, with these changes differing also between tectonic regimes.

For instance, plate interiors and active continental regions show evolving proportions of normal, reverse, and strike-slip mechanisms as magnitude increases, while spreading ridges exhibit a marked reduction in normal faulting at higher magnitudes. Subduction trenches, by contrast, display more stable focal mechanism distributions across magnitude bins. This variability implies that the probability of observing a particular focal-mechanism class in a given region is influenced not only by its tectonic regime but also by the magnitude window of the sample used. Therefore, this dependence should be incorporated into models forecasting focal mechanisms for target magnitude events, like for example for tsunami hazard, where typically the interest is on  $M > 6.5$  events.

If magnitude is not accounted for, probabilistic forecasts are dominated by small-magnitude events, which are far more numerous, biasing the resulting posterior distributions and masking the true characteristics of larger, more impactful earthquakes. The results from the Mediterranean region application confirm this: limiting the analysis to larger magnitudes leads to posterior distributions that emphasize reverse faulting and reduce apparent extension or strike-slip mechanisms in many zones, while including all magnitudes gives a more diffuse and less representative spatial pattern.

Comparisons using the Kagan angle indicate that spatial differences between distributions constructed using all events versus only large events are most pronounced in areas with active faults and recorded large earthquakes; on the other hand, in regions lacking faults or large events, distributions remain

essentially unchanged and reflect prior assumptions. The fact that the Kagan angle often differs significantly from zero demonstrates that considering the contribution of different magnitude ranges substantially alters the posterior distribution compared to using all magnitudes indiscriminately, leading to a more realistic and physically meaningful forecast of focal mechanisms.

Our Bayesian framework and its implementation code, combining physically constrained discrete priors with updated observational and geological data, offers a robust and flexible approach to producing target forecasts of focal mechanism, accounting for tectonics, known faults and target magnitude range. A key strength of this code is its modularity: users can select and customize any input dataset—such as earthquake catalogs, fault inventories, tectonic regionalization, and magnitude ranges—making the framework easily adaptable and applicable to any geographical region worldwide.

Future work should include quantitative testing of model performance based on forward testing, given the intrinsic lack of sufficient data, and the development of an open-source, user-friendly software package, enabling the broader scientific and hazard-assessment community to easily apply and adapt it to their scopes.



## DIFFERENCES IN FORESHOCK IDENTIFICATION BETWEEN NN AND ETAS

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I contributed to the conceptualization of the study, curated and analyzed the data, carried out the investigation, developed methodology and software, created visualizations, and co-wrote both the original draft and the review/editing of the manuscript.

## 7.1 Abstract

Foreshocks—small earthquakes preceding a larger one—are difficult to identify in real time given that they are statistically similar to background seismicity. This challenge is consistent with the magnitude-independent assumption in the ETAS model, whereby the size of the next earthquake is randomly drawn from a common magnitude distribution. In this chapter, we explicitly assess how well the nearest neighbor (NN) approach can reproduce the clustering patterns generated by ETAS, which we treat as the null hypothesis. Using synthetic catalogs, we compare the performance of NN against ETAS in recovering triggering relationships.

Our results highlight that, although NN produces spatially compact clusters, it systematically underperforms in approximating ETAS: it misses a large fraction of ETAS-defined foreshocks, overestimates the occurrence of sequences without foreshocks, and exaggerates the dependence of foreshock number on mainshock magnitude. Moreover, NN's strong emphasis on short-term temporal proximity prevents it from capturing temporally extended sequences that are well represented by ETAS.

Overall, this work provides a quantitative evaluation of the ability of NN to reproduce the reference model ETAS, revealing clear limitations in its capacity to mimic the true structure of earthquake clustering. Future research will explore the implications of these findings for real seismicity.

## 7.2 Introduction

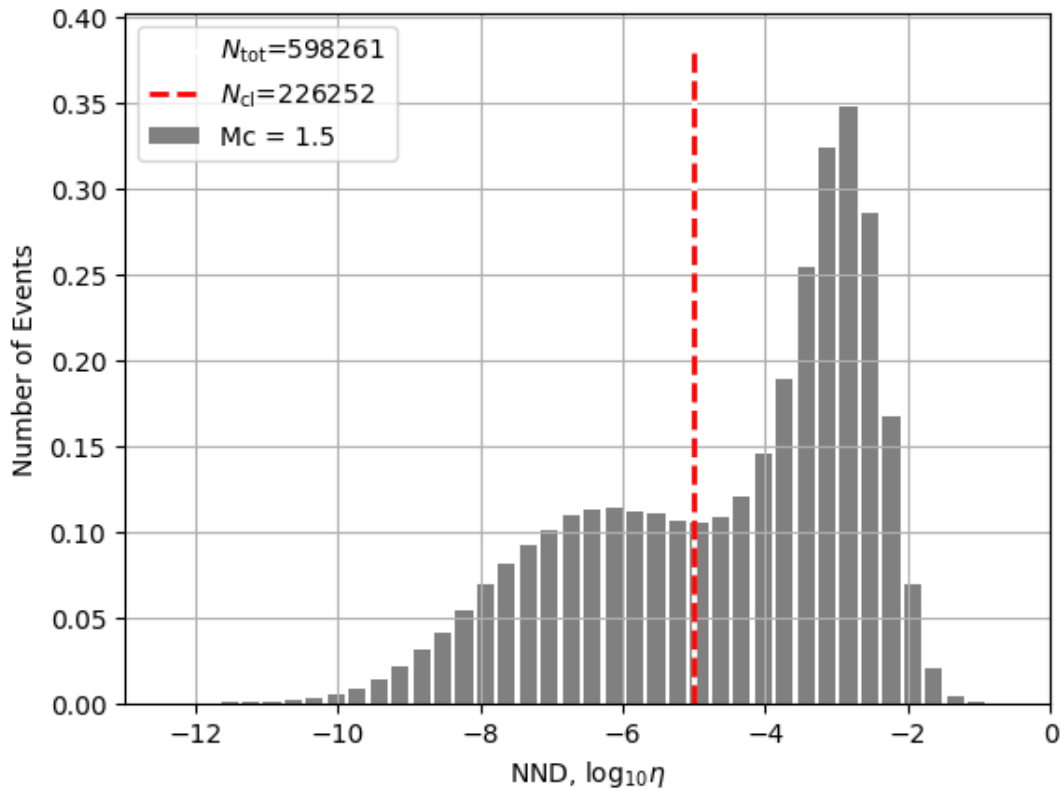
Previous chapters have shown how many apparent anomalies in seismicity statistics can arise from methodological effects, structural heterogeneities, or physical conditions of the lithosphere, rather than reflecting genuine precursor signals. In this context, Chapter 7 addresses one of the debated topics in seismology: the identification of foreshocks.

Large earthquakes are often preceded by smaller events that, in hindsight, are classified as foreshocks. Well-known examples include the 2009 L'Aquila, the 2011 Tohoku, and the 2019 Ridgecrest earthquakes. Understanding and identifying foreshocks is of considerable scientific interest, as their detection in real-time can increase the probability of a subsequent larger event (Agnew and Jones 1991).

Yet, real-time detection is extremely challenging: most of empirical evidence show that foreshocks are statistically indistinguishable from background seismicity (Jordan 2011; Lippiello, *et al.* 2017). The present work represents a preliminary step, using synthetic catalogs, to compare clustering approaches and to assess how methodological choices shape the definition of foreshocks.

Since earthquakes cluster in space and time (see Chapter 1), clustering techniques are commonly employed to identify seismic sequences and distinguish them from the independent background activity. Among these approaches, the Nearest Neighbor (NN) method (Zaliapin, *et al.* 2008) has become one of the most widely used tools, owing to its deterministic

formulation and relatively easy implementation. The method relies on a combined space-time-magnitude distance between events to determine likely parent–child relationships. Figure 7.1 illustrates a typical histogram of these distances in a catalog. Two distinct modes usually emerge: a clustered mode, corresponding to closely related events such as aftershocks, and a background mode, representing independent, Poissonian seismicity. A cutoff value,  $\eta_0$ , separates these two modes, and in practice, links with distances larger than  $\eta_0$  are removed, yielding well-defined clusters. This threshold is fundamental for NN, as it determines which events are considered part of the same sequence and which belong to the background, directly shaping the parent–child assignments that underpin foreshock identification.



**Figure 7.1** *Histogram of the nearest parent space–time–magnitude distance in the catalog.*

Two distinct modes typically emerge in an earthquake catalog: a clustered mode (left) and a background mode (right). The clustered mode reflects Omori-type aftershock clustering (generally corresponding to “nearer” events), while the background mode represents the underlying Poissonian background process. Earthquakes belonging to the background mode are, by observation, not triggered by previous events. The cutoff value  $\eta_0$  separates these two modes: in practice, all links between earthquakes with a distance larger than  $\eta_0$  are removed, yielding distinct clusters of events.

The NN algorithm links each earthquake to its most related predecessor in a combined space–time–magnitude domain, producing compact clusters with well-defined parent–child relations (see “Nearest-neighbor”). Because of its increasing use in foreshock studies, it is important to evaluate whether NN can recover triggering relationships.

Recent comparative studies illustrate these differences. Varini *et al.* (2020) applied NN and ETAS to Northern Italy, finding that ETAS produced larger, temporally extended clusters, while NN generated more compact ones. Manganiello *et al.* (2023) used NN and a spatio-temporal method named STW in Southern California and compared the results with ETAS-simulated catalogs treated as a null hypothesis. They reported that both methods identified more foreshocks than ETAS predicted, particularly for mainshocks with magnitudes below 5.5 and in high heat-flow regions—patterns not reproduced by ETAS, even when calibrated for California.

To provide a benchmark, we compare NN classifications against synthetic catalogs generated with the simpleETAS model (Mancini and Marzocchi 2023), a simplified formulation of ETAS that preserves the essential physics of earthquake cascades (see “[Catalog simulation](#)”).

In this framework, ETAS represents the “true” process generating seismicity. Foreshock–mainshock relations identified through the parental links of the model serve as the ground truth. By restricting the analysis to direct parent–mainshock relations, we can test whether NN is capable of correctly identifying foreshocks and reproducing their statistical properties.

### 7.3 Results

#### 7.3.1 Event tree structures

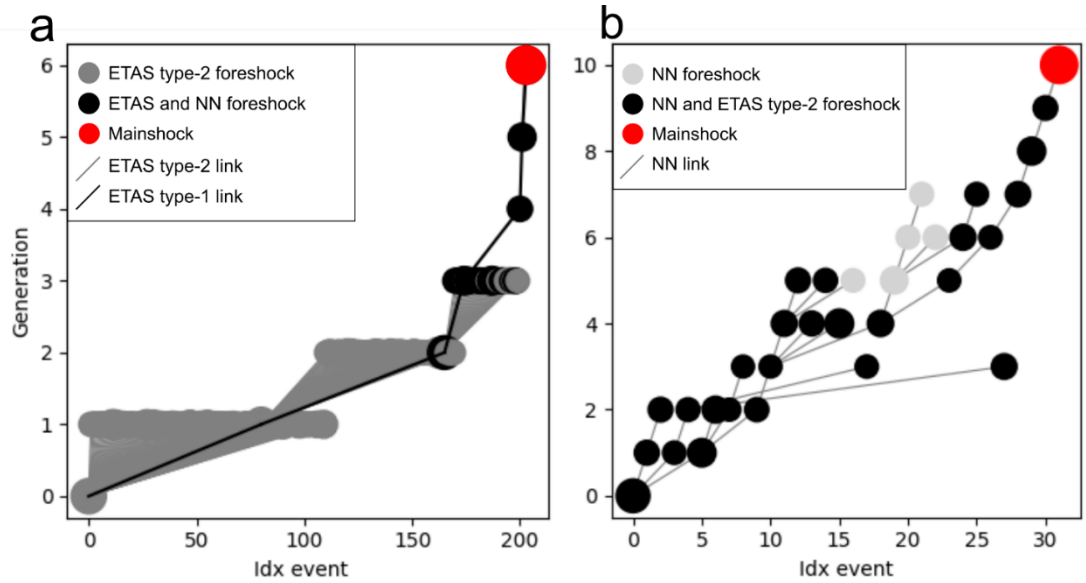
We first identify the ETAS foreshocks as in “Mainshock and foreshock identification” obtaining type-1, defined as the direct chain of events between first foreshocks and its mainshock; and type-2, which comprehends type-1 events and all the first generations events linked to them.

Figure 7.2 illustrates event trees derived from synthetic catalogs using the two clustering methods: ETAS (panel a) and NN (panel b). Nodes represent earthquakes classified as foreshocks or mainshocks, with colors indicating their classification (grey: unique to each method; black: common to both; red: mainshocks). Lines show the parent-child links determined by each method.

The structure of the event trees highlights fundamental differences between the two approaches. By construction, ETAS produces linear chains that explicitly reflect the generational sequence of triggered events (see “Mainshock and foreshock identification”). In contrast, NN generates more complex and branching networks, often containing a larger number of events. However, NN does not identify all the foreshocks recognized by ETAS (either type-1 or type-2). In fact, only about 40% of ETAS type-1 sequences are fully recovered by NN, indicating that a substantial fraction of ETAS-defined foreshocks are either missed or misclassified by NN.

When considering the recovery per mainshock magnitude class, the proportion of ETAS type-1 sequences fully recognized by NN is consistently below 40%: for mainshocks in the [4.0, 4.5) range, 77 out of 194 sequences ( $\approx 39.7\%$ ) are recovered; for [4.5, 5.0), 29 out of 74 sequences ( $\approx 39.2\%$ ); for [5.0, 5.5), 12 out of 34 sequences ( $\approx 35.3\%$ ); and for [5.5, 6.0), only 1 out of 3 sequences ( $\approx 33.3\%$ ).

These percentages are nearly halved for ETAS type-2 sequences, which, by definition, include a larger number of events that indirectly contribute to the occurrence of the next event.



**Figure 7.2 Event trees from a representative synthetic sequence illustrating foreshocks and mainshock (with ETAS and NN).**

(a) the ETAS model, which produces clear generational parent-child sequences, and (b) the Nearest Neighbor (NN) method, which generates more spatially compact but branching networks. Node colors indicate foreshock classification (grey: unique to method, black: common to both methods) and red indicates mainshocks. Line represents the parental links constructed by each method: in panel a, black lines indicate the direct generational link between the first foreshock and the mainshock which identifies ETAS type-1 foreshocks, the grey lines indicate the ETAS link between each ETAS type-1 foreshock and the first generation of events linked to each foreshock (ETAS type-2). In panel b, the lines indicate the parental relationship between each event as defined by the NN method.

An additional difference between the two methods concerns the fraction of sequences classified as having no foreshocks. As shown in Table 7.1, NN systematically overestimates this proportion compared to ETAS, with a consistent offset across all magnitude classes.

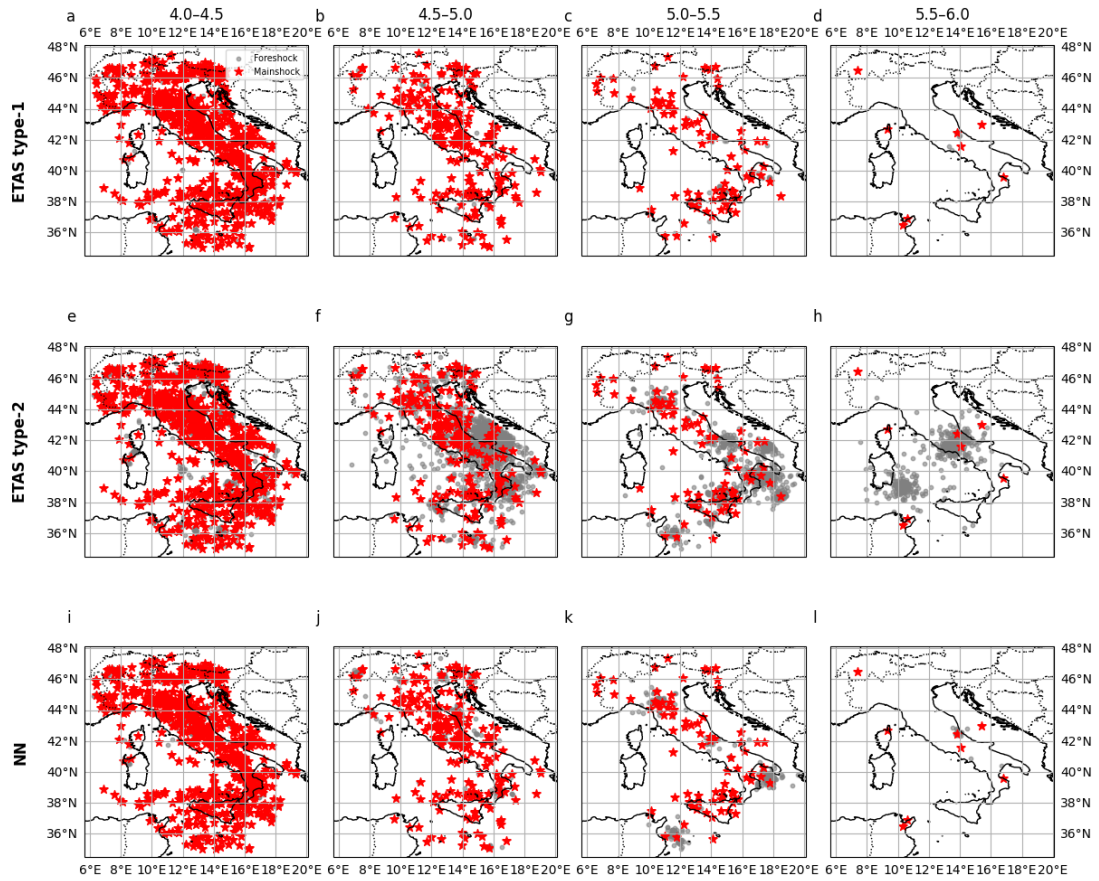
*Table 7.1 Percentages of sequences without foreshocks.*

|                 | NN  | ETAS |
|-----------------|-----|------|
| <b>All</b>      | 84% | 71%  |
| <b>M4.0-4.5</b> | 85% | 74%  |
| <b>M4.5-5.0</b> | 81% | 65%  |
| <b>M5.0-5.5</b> | 82% | 61%  |
| <b>M5.5-6.0</b> | 75% | 63%  |

Beyond the presence or absence of precursors, the three approaches also diverge in the number and distribution of foreshocks per mainshock. Under ETAS, most type-1 foreshocks are associated with larger mainshocks (42.5% for M5.5–6.0, 24.6% for M5.0–5.5), whereas NN concentrates nearly half of all foreshocks in the M5.0–5.5 class (45.6%), followed by 38.4% in the highest magnitude range. In contrast, ETAS type-2 shows an even stronger preference for the largest mainshocks, with more than three-quarters of foreshocks (75.1%) associated with the M5.5–6.0 range, while lower magnitudes account for only a minor fraction (11.3% in M5.0–5.5, 12.1% in M4.5–5.0, and just 1.5% in M4.0–4.5).

### 7.3.2 Spatial and temporal distributions of foreshocks

The spatial distributions of sequences with at least one foreshock (Figure 7.3) emphasize the first major difference between the methods. ETAS detects a larger number of sequences containing foreshocks, but they are sparse and often involve only one or a few events. NN, in contrast, identifies fewer sequences, but when it does, these typically contain multiple foreshocks concentrated near the mainshock.



**Figure 7.3** *Spatial distribution of sequences with at least one foreshock. The mainshocks (GK method, see “Mainshock and foreshock identification”) for each category (columns) are indicated with a red star. a-d) ETAS type-1 foreshocks; e-h) ETAS type-2 foreshocks; i-l) NN foreshocks (grey dots).*

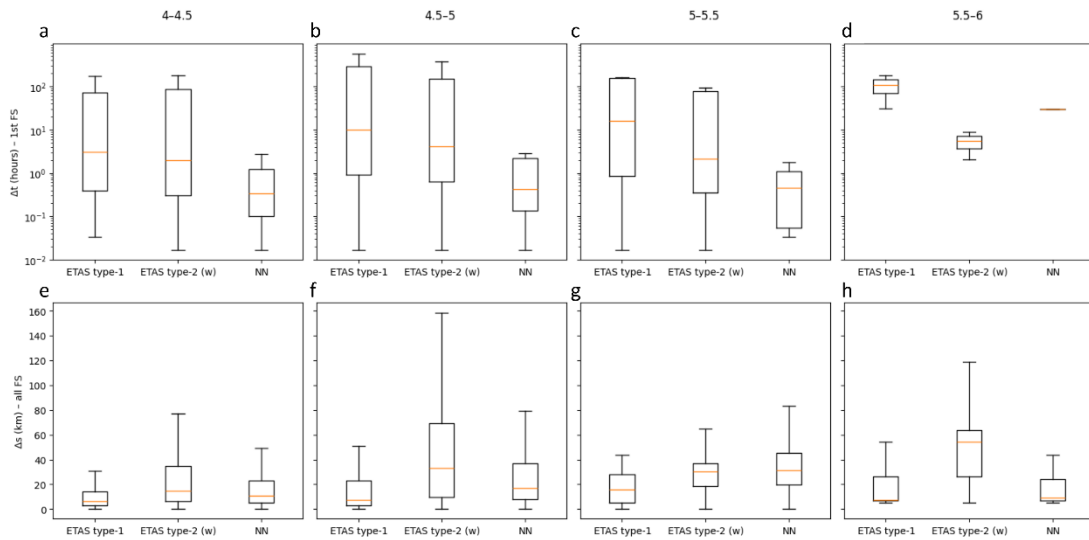
To analyze the spatio-temporal characteristics of ETAS type-2 sequences, we weighed them according to the magnitude of the event using the relations defined by the NN method (eqs. 7.3 and 7.4) to reduce the contribution of smaller events that are less likely to generate subsequent events.

The temporal and spatial differences between foreshocks and mainshocks clarify these patterns (Figure 7.4).

Inter-event times between the first foreshock of each sequence and its mainshock (a-d) show that NN identifies the closest precursor in time, resulting

in systematically shorter  $\Delta t$ , while ETAS type-1 tends to capture much earlier foreshocks. ETAS type-2 again reduces this bias, placing the first foreshock closer to the mainshock than ETAS type-1, but not as close as in NN. In this case ETAS type-2 foreshock is the same as ETAS type-1, the only difference lies in the weighting assigned to the event.

Spatial distances (e-h) remain small for NN and ETAS type-1, but ETAS type-2 sequences often span much larger distances. This indicates that, while NN focuses on near-mainshock foreshocks and ETAS type-1 allows temporally scattered but still spatially compact precursors, ETAS type-2 captures a broader, more spatially dispersed set of foreshocks, highlighting differences in how each method represents spatiotemporal clustering even when weighted by the magnitude.



**Figure 7.4** Box-plots showing the temporal and spatial differences. Between each foreshock and its mainshock (a-d and i-l) and between the first foreshock and its mainshock (e-h) for each mainshock magnitude class.

## 7.4 Discussion

The analyses presented in this chapter highlight fundamental differences between the ETAS and NN clustering approaches when applied to synthetic catalogs. Because ETAS represents the generative process of seismicity in our study, it provides a clear benchmark to evaluate the ability of NN to identify foreshocks and reproduce their statistical properties. Our results indicate that NN, although widely used and computationally convenient, fails to fully capture the underlying triggering relationships encoded in the ETAS model.

A central finding of this work is that NN systematically under-recovers foreshocks defined by ETAS. Only about 40% of ETAS type-1 foreshock sequences are fully identified by NN across all magnitude ranges, and recovery is even lower for type-2 sequences, which additionally include first-generation triggered events. The origin of this discrepancy lies in NN's strong preference for very short inter-event times: the method links each event to the closest predecessor in a combined space–time–magnitude metric, inherently favoring compact and temporally narrow clusters. As a result, earlier or more temporally scattered precursors—common in ETAS sequences—are routinely discarded by NN.

This limitation does not apply only to the specific case of temporally dispersed foreshocks. Rather, it is the underlying mechanism that explains most of the divergences documented in this chapter. NN emphasizes short-term proximity causing the over estimation of sequences without foreshocks, the concentration

of foreshocks very close to the mainshock (both in space and time). It also fails to recover ETAS type-2 sequences, which naturally include spatially and temporally extended generations.

In all cases, NN preferentially selects only the most immediate precursors, thereby suppressing the more diffuse triggering chains that ETAS produces. Thus, the poor recovery of temporally scattered precursors is not an isolated observation but the fundamental process driving nearly all major results in this chapter.

These findings align with and extend previous comparative studies. Varini *et al.* (2020) reported that NN yields compact clusters that are temporally concentrated, while ETAS captures longer chains of triggering. Manganiello *et al.* (2023) also showed that NN tends to overemphasize short-term clustering when applied to California. However, both studies relied on real data, where the true triggering structure is unknown, making it difficult to quantify the accuracy of each method. Instead, our work provides a fully quantitative evaluation of NN performance against a known ground truth, thanks to the use of synthetic catalogs generated with ETAS. This controlled setting allows us to directly measure how often and under which conditions NN succeeds or fails in recovering foreshock–mainshock relations.

The implications of these discrepancies are significant. Because NN tends to produce clusters that are denser and more tightly bound to the mainshock in space and time, it may overestimate the predictive value of short-term

precursors and underrepresent more complex triggering sequences. Conversely, ETAS, by allowing earlier and spatially scattered foreshocks, reflects a broader range of triggering behaviors, more consistent with the stochastic nature of earthquake cascades.

Our conclusions are based on a limited set of synthetic catalogs and on a particular ETAS formulation (simpleETAS, Mancini and Marzocchi 2023), where the definitions of type-1 and type-2 foreshocks are inherently deterministic. While this allows a clear ground truth for benchmarking NN, it does not capture the probabilistic nature and potential overlap of real seismic triggering. Future work should extend this analysis to larger ensembles of simulations and to real catalogs and explore probabilistic stochastic declustering approaches (e.g., Bayliss, *et al.* 2019) that allow events to have overlapping ancestry. Such methods could provide a more realistic representation of multi-generational triggering and help assess whether the discrepancies documented here persist when the strict parent–child assignments of ETAS are relaxed. This would provide a valuable bridge between model-based inferences and empirical observations and further clarify the extent to which NN can be reliably used to study foreshocks in real time.



## Part 3

# CONCLUSION



## DISCUSSION AND CONCLUSIONS

### 8.1 Discussion

A first unifying result concerns the pervasive influence of methodological artifacts in producing patterns that might otherwise be interpreted as physical precursors. In Chapter 2, I show that magnitude correlation and anomalously low  $b$ -values—features often linked in the literature to preparatory phases before large earthquakes—arise almost entirely from short-term catalog incompleteness. This finding supports earlier studies (Kagan 2004; Helmstetter 2006; Marzocchi, *et al.* 2020) about many reported anomalies in seismic sequences that could be artifacts of incomplete or inconsistently processed data.

This results directly connect with the introductory discussion about the role of chance in earthquake occurrence. What is sometimes interpreted as a physical signal reflecting change in the earthquake-generating process may instead be a manifestation of noise, in the broadest sense: undetected small earthquakes, measurement uncertainties, and methodological choices. The implication is not

## DISCUSSION AND CONCLUSIONS

that earthquakes occur randomly, but that randomness often enters through imperfections in the data rather than the underlying physics.

Chapters 3, 4 and 5, collectively demonstrate that when methodological biases are controlled for, spatial heterogeneities emerge as the dominant source of variability in earthquake size distributions. The case study of central Italy (Chapter 3) provides a good example: what had been interpreted in previous work as precursory temporal increase in the  $b$ -value before the Norcia earthquake is instead explained by the alternating activation of two fault structures with distinct geometries, orientations and magnitude distributions. This result reveals the downside of aggregating seismicity across heterogeneous volumes and echoes the longstanding concerns regarding the non-stationarity of seismic catalog when physical structures are not properly isolated.

At the global scale, the analyses in Chapters 4 and 5 extend this concept by showing that  $b$ -values and corner magnitudes are not universal but depend jointly on tectonic environment, thermal regime, and fault kinematics. While previous studies had suggested individual correlations, the results of this thesis show that no single factor can explain the observed variability. Instead, earthquake size distributions reflect a multi-parameter interplay between large-scale geodynamic forcing and local fault architecture.

This finding indicates that even if magnitudes are statistically independent at the events scale (Chapter 2), the parameters of the magnitude distribution themselves are shaped by the underlying physics.

## DISCUSSION AND CONCLUSIONS

Chapter 6 demonstrates how this combined understanding of physics and statistics can improve operational forecasting. By incorporating magnitude dependence into focal-mechanism forecasts, I show that fault kinematics vary systematically with earthquake size and tectonic context, contradicting assumptions commonly used in seismic and tsunami hazard models. This magnitude dependence had been largely overlooked in previous studies that relied on stationary distributions of focal mechanisms.

Finally, Chapter 7 addresses one of the most debated questions in seismology: whether foreshocks contain predictive information about large earthquakes. By comparing NN and ETAS declustering on synthetic catalogs created with the ETAS model, I show that much of the variability in foreshock statistics arises not from physical differences but from the declustering method itself. This finding reinforces the cautionary perspective introduced in Chapter 1: foreshocks may still reflect physical processes in specific cases, but our ability to recognize them in real time is fundamentally limited by methodological ambiguity.

This thesis also highlights several open challenges: first, the exact relationship between thermal structure, stress state, and magnitude–frequency parameters remain incompletely understood; laboratory and geodynamic modeling could help clarify causal mechanisms.

## DISCUSSION AND CONCLUSIONS

Second, improving the detection of small earthquakes—particularly in the minutes following large events—would reduce STI and enhance the reliability of real-time forecasts.

Finally, the ambiguity in foreshock identification invites future work on hybrid models that combine physical constraints with machine-learning clustering.

### 8.2 Conclusions

While each chapter of this thesis has presented specific findings and included its own discussion, here I bring together the main contributions in their broader scientific context. The main theme of this thesis has been to identify the physical and methodological factors that control earthquake occurrence and characteristics, and to assess how these factors shape our ability to forecast future seismicity reliably.

The thesis addressed four correlated topics: (i) magnitude correlations and catalog completeness (Chapter 2), (ii) spatial heterogeneity of seismicity and *b*-value variations (Chapter 3), (iii) the influence of thermal regimes, tectonic settings, and fault kinematics on magnitude–frequency distributions (Chapters 4 and 5), and (iv) magnitude dependence in focal mechanism forecasts (Chapter 6). Finally, Chapter 7 investigated the statistical identification of foreshocks, comparing two declustering approaches.

The results demonstrate that some apparent anomalies in earthquake statistics often arise from methodological or catalog-related artifacts rather than from

## DISCUSSION AND CONCLUSIONS

genuine physical precursors. For example, the detection of magnitude correlations and anomalously low  $b$ -values during the Ridgecrest and central Italy sequences was shown to be a consequence of short-term incompleteness and the mixing of distinct fault structures, rather than precursory changes in stress. This highlights the critical importance of catalog consistency and resolution in seismological studies.

At the same time, the thesis revealed physical controls on earthquake size distributions. The joint role of heat flow, tectonic regime, and faulting style was shown to modulate both the relative abundance of small earthquakes and the probability of larger events, producing systematic variations in  $b$ -values and corner magnitudes. These findings emphasize that earthquake statistics cannot be treated as universal but must be conditioned on local geodynamic and kinematic factors.

Building on this, the development of a Bayesian framework for focal mechanism forecasts demonstrated that earthquake mechanisms vary systematically with magnitude and that ignoring this dependence biases hazard assessments. Incorporating magnitude dependence produces more physically consistent forecasts and provides improved input for seismic and tsunami hazard models.

Finally, the analysis of foreshocks demonstrates that the definition of foreshock activity is highly sensitive to the declustering method used to extract background and triggered events. In this work, I generated synthetic catalogs

## DISCUSSION AND CONCLUSIONS

using a forward ETAS model and then identified foreshocks using two different approaches: (i) the ETAS-based classification, which is directly known from the simulation, and (ii) the Nearest Neighbor (NN) method, which is widely used in empirical studies. The differences between these two classifications show that foreshock statistics are strongly method-dependent: the NN approach systematically misses some of the triggered sequences that the ETAS model predicts, leading to incomplete or distorted foreshock catalogs. Thus, the observed discrepancies do not reflect different physical processes, but rather the limitations of the NN algorithm in recovering the triggering structure present in the synthetic data. For this reason, great caution is needed when interpreting NN-derived foreshock patterns as evidence for genuine preparatory phenomena.

Taken together, the contributions of this thesis advance our understanding of how both physical processes and methodological choices affect the statistical properties of seismicity. They also provide practical frameworks to improve earthquake forecasting, hazard assessment, and the interpretation of earthquake precursors.

Returning to the question raised at the start of this thesis—*does God play dice?*—the work presented here suggests that while randomness is an intrinsic component of seismicity, systematic physical controls also leave their imprint. Exploring this balance between chance and determinism will remain a central challenge for future research.



## Part 4

# APPENDIX AND BIBLIOGRAPHY



# 9

## SUPPORTING INFORMATION FOR CHAPTER

## 2

This section is published as Supporting Information of

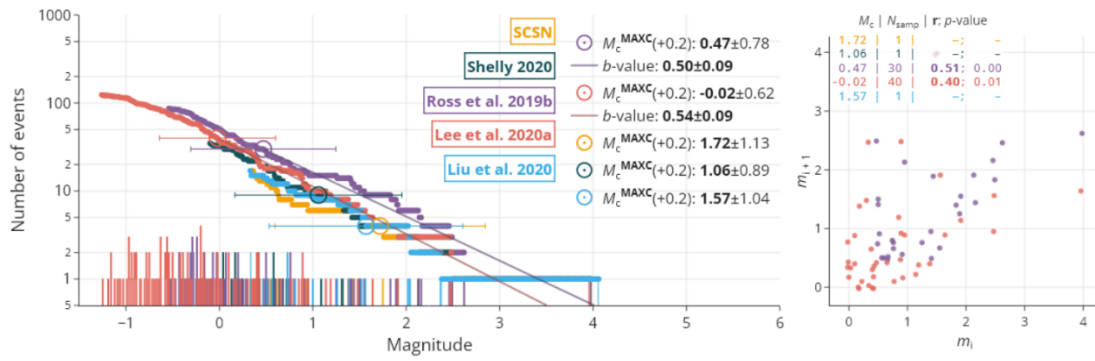
Corrado, P., Herrmann, M., and Marzocchi, W. (2025). Earthquake Magnitude Correlations Expose Short-Term Catalog Incompleteness. *Seismological Research Letters*, 96(2A), 909-919.

**Table 9.1 Comparison of magnitude statistics.**

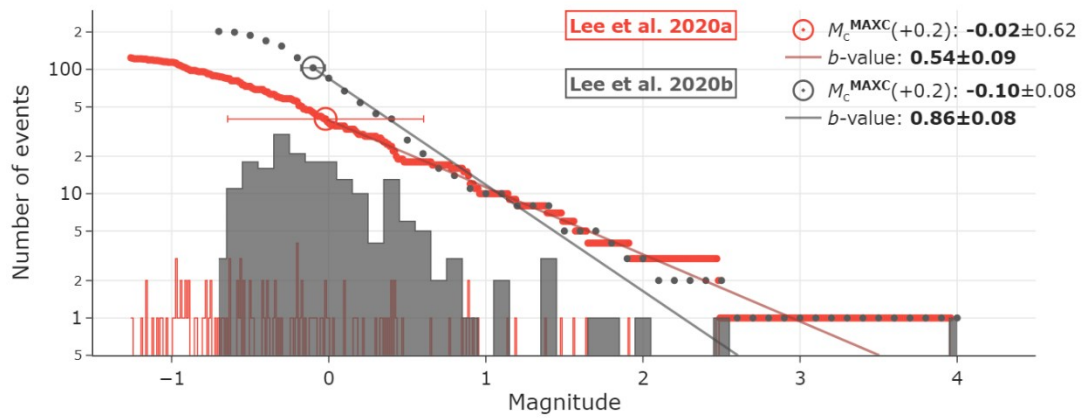
Between the real (2019 Ridgecrest foreshocks) and synthetic sequences with applied STI as obtained with different “Data and Methods” and for different data sets.

|                                                 |             | $b$       | $b^+$       | Pearson              |                                   | Spearman               |                                     |
|-------------------------------------------------|-------------|-----------|-------------|----------------------|-----------------------------------|------------------------|-------------------------------------|
|                                                 |             |           |             | $r$  <br>$p$         | $r (\Delta M^+)$  <br>$p$         | $r_s$  <br>$p$         | $r_s (\Delta M^+)$  <br>$p$         |
| Ridgecrest foreshock sequence                   | $M_L$       | 0.54±0.09 | 0.55±0.07   | 0.40  <br>0.01       | -0.03  <br>0.81                   | 0.37  <br>0.02         | 0.09  <br>0.52                      |
|                                                 | $M_W$ (G09) | 0.77±0.12 | 0.84±0.11   | 0.37  <br>0.02       | -0.04  <br>0.78                   | 0.37  <br>0.02         | 0.10  <br>0.48                      |
|                                                 | $M_W$ (D17) | 0.80±0.13 | 0.82±0.11   | 0.40  <br>0.01       | -0.04  <br>0.80                   | 0.37  <br>0.02         | 0.10  <br>0.49                      |
|                                                 |             |           |             |                      |                                   |                        |                                     |
|                                                 |             | $\bar{b}$ | $\bar{b}^+$ | $\bar{r}$  <br>$p^F$ | $\bar{r} (\Delta M^+)$  <br>$p^F$ | $\bar{r}_s$  <br>$p^F$ | $\bar{r}_s (\Delta M^+)$  <br>$p^F$ |
| Synthetic sequences                             |             | 0.94±0.01 | 0.94±0.01   | 0.00  <br>0.93       | -0.01  <br>0.74                   | 0.00  <br>0.92         | -0.02  <br>0.89                     |
|                                                 | with STI    | 0.82±0.01 | 0.84±0.01   | 0.12  <br>0.00       | 0.00  <br>0.71                    | 0.08  <br>0.00         | -0.01  <br>0.47                     |
|                                                 |             |           |             |                      |                                   |                        |                                     |
|                                                 |             | $b$       | $b^+$       | $r^c$  <br>$p^c$     | $r^c (\Delta M^+)$  <br>$p^c$     | $r_s^c$  <br>$p^c$     | $r_s^c (\Delta M^+)$  <br>$p^c$     |
| Combined magnitude pairs of synthetic sequences |             | 0.94±0.01 | 0.94±0.01   | 0.00  <br>0.69       | 0.00  <br>0.53                    | 0.00  <br>0.68         | 0.01  <br>0.60                      |
|                                                 | with STI    | 0.80±0.01 | 0.87±0.01   | 0.20  <br>0.00       | 0.01  <br>0.17                    | 0.17  <br>0.00         | 0.02  <br>0.06                      |

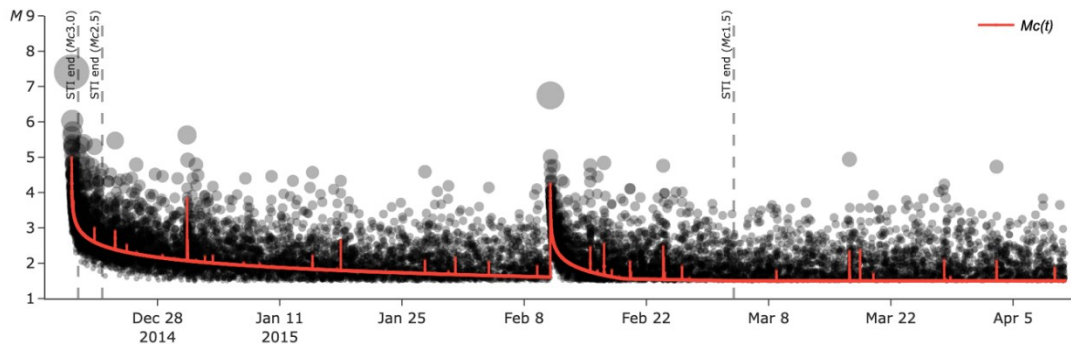
For the real catalog, the analysis is performed for three different magnitudes: the original  $M_L$ , and their conversion to  $M_W$  using Grünthal et al. 2009 (G09) and a bilinear relation (Deichmann, 2017, D17), see “Data and Methods”. The first two columns display the estimated  $b$ -value and  $b$ -positive ( $b^+$ ) estimate (van der Elst 2021). The remaining columns present the Pearson correlation coefficients ( $r$ ) and Spearman correlation coefficients ( $r_s$ ) with their corresponding  $p$ -values—once for the plain magnitudes and once using only positive magnitude differences ( $\Delta M^+$ ). For the synthetic sequences, I perform the same analysis in two different ways (see “Data and Methods”): (i) considering all the sequences separately, therefore calculating the average  $b$ -value and  $b$ -positive, average correlation coefficient ( $\bar{r}$ ), and the combined  $p$ -value using the Fisher method ( $p^F$ ); (ii) combining all the magnitude pairs of the sequences into two vectors and calculating the (combined) correlation coefficient ( $r^c$ ) and the corresponding  $p$ -value ( $p^c$ ). Significant correlations ( $p$ -value < 0.05) are highlighted in bold.



**Figure 9.1** Magnitude statistics of the 2019 Ridgecrest foreshock sequence using various catalogs.

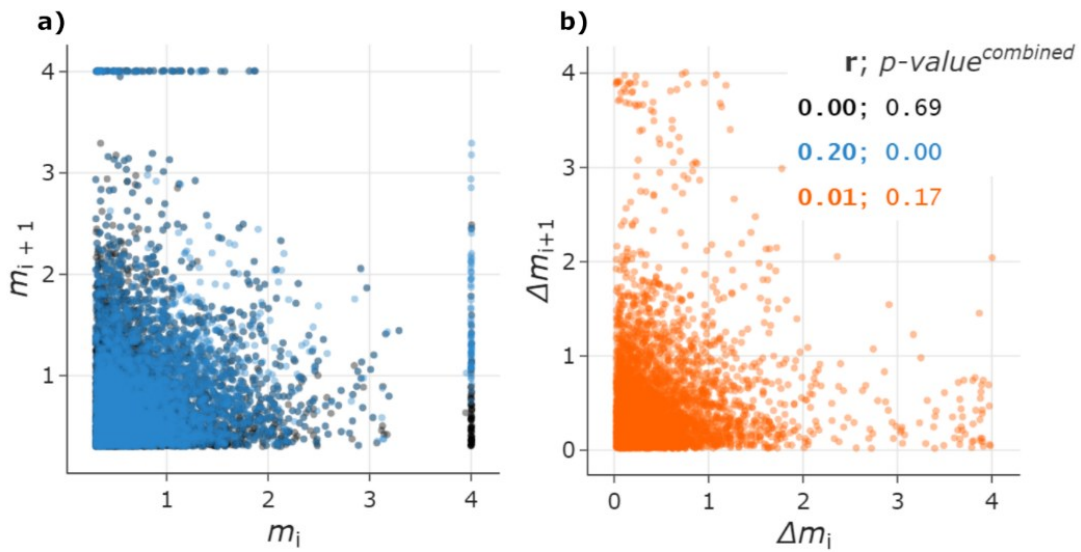


**Figure 9.2** Magnitude statistics of the 2019 Ridgecrest foreshock sequence (comparison with Lee et al. (2020b) catalog (which has an inconsistent magnitude scale)).

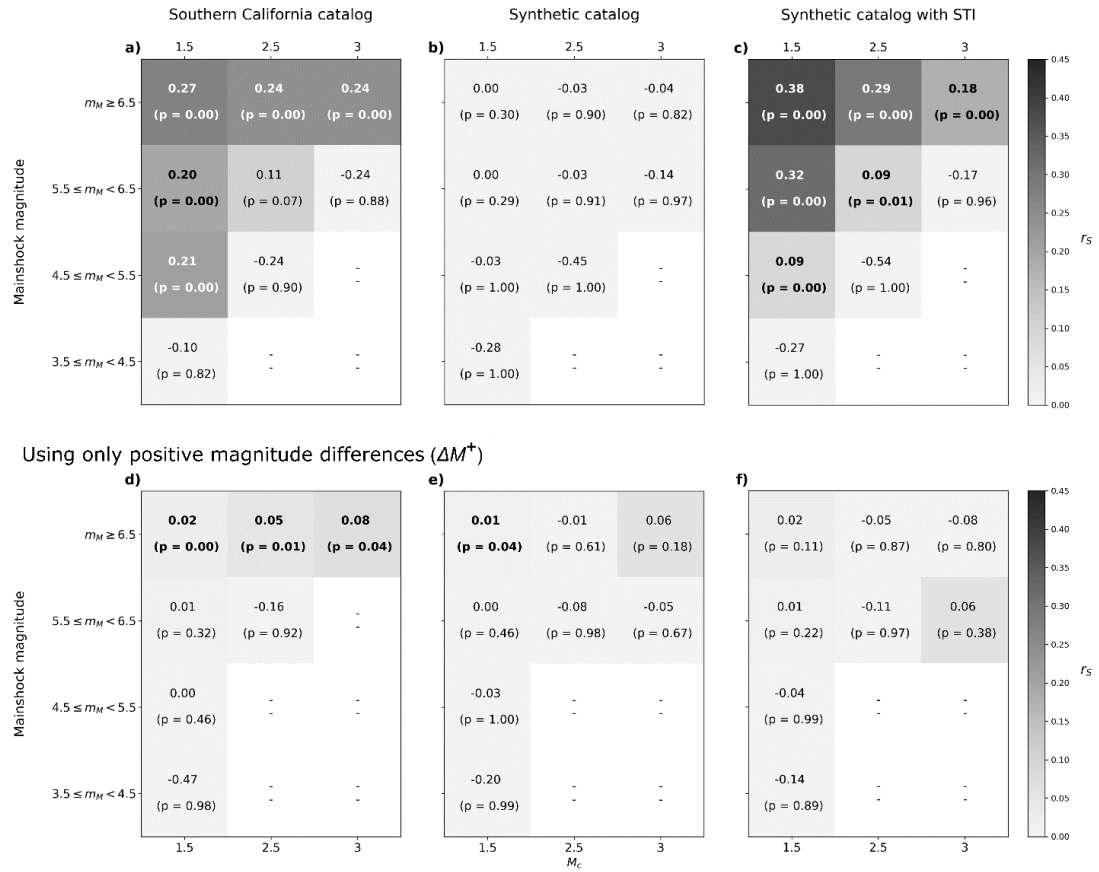


**Figure 9.3** *Timeline of a simulated sequence with applied STI (see “[Data and Methods](#)”).*

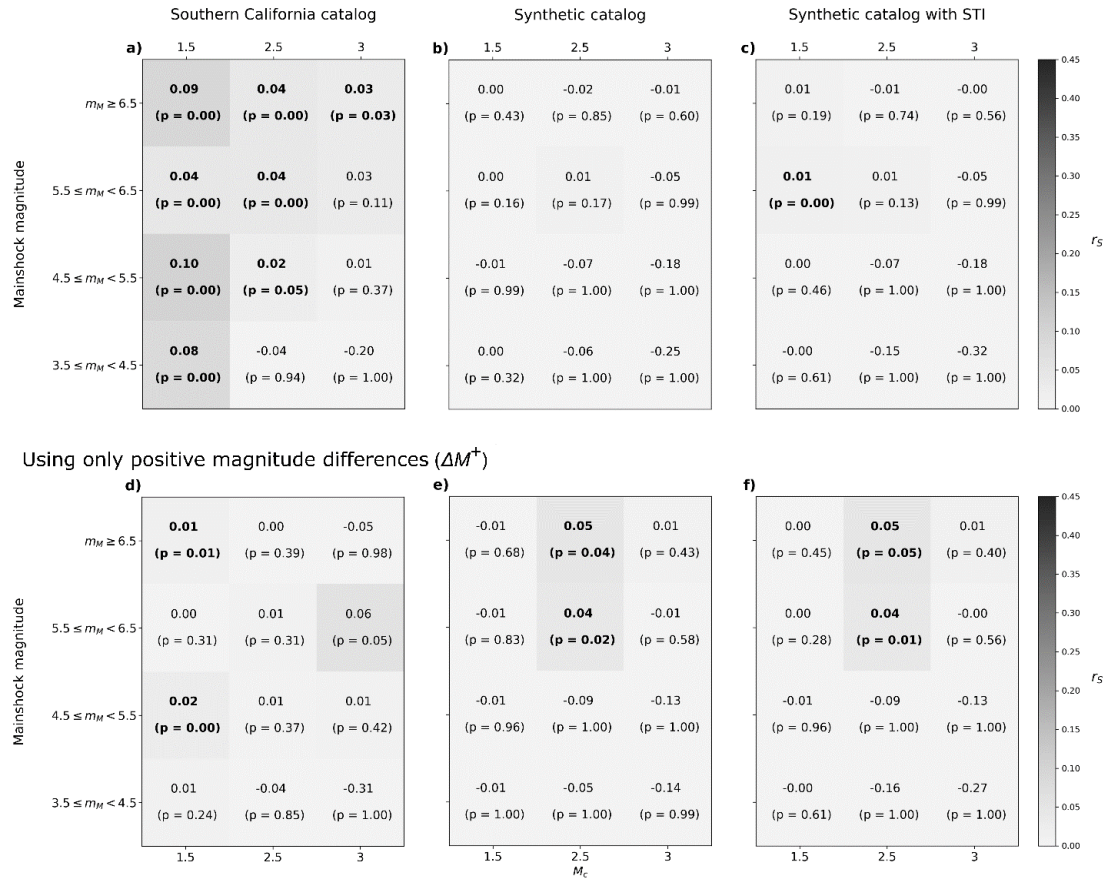
The red curve represents the variation of the completeness magnitude  $M_c(t)$  as calculated for each event with the STI relation of Helmstetter et al. (2006); see “[Data and Methods](#)”. The vertical dashed lines indicate the end of the STI period of the mainshock ( $M_{7.4}$ ) according to the Helmstetter relation for three different completeness magnitudes  $M_c$  (1.5, 2.5 and 3.0).



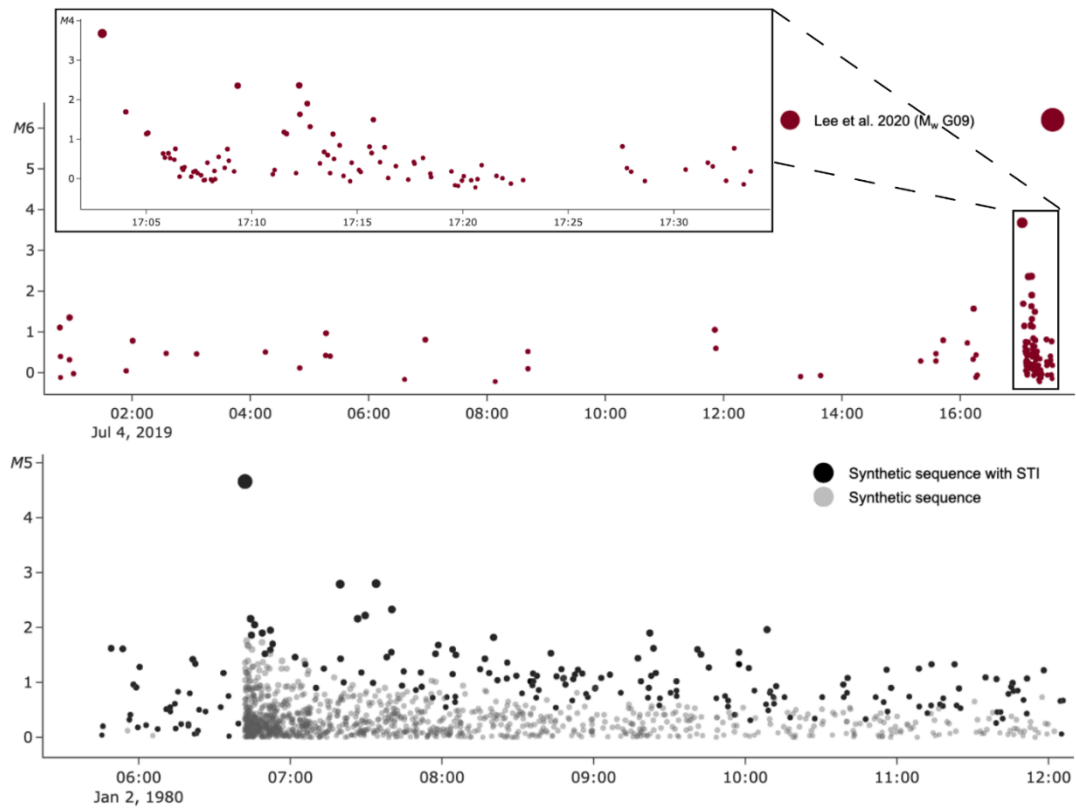
**Figure 9.4** *Magnitude statistics of synthetic sequences obtained by combining all (normalized) magnitude pairs of the sequences into two vectors,  $m_i$  and  $m_{i+1}$ .*



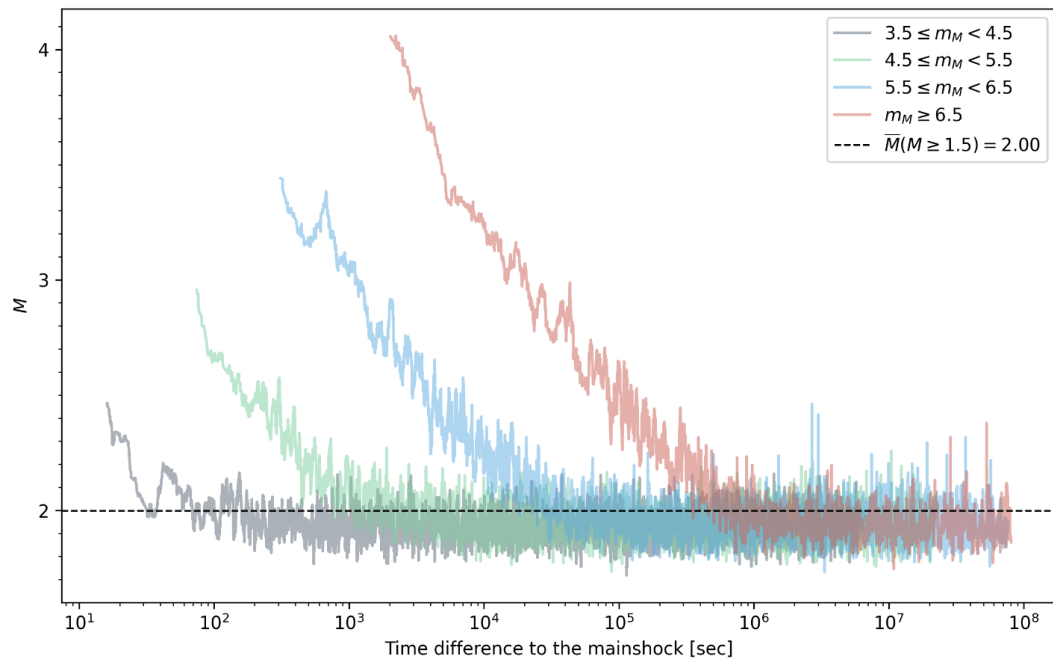
**Figure 9.5** Investigating magnitude correlation in the real and synthetic catalog (STI period) using the Spearman correlation coefficient.



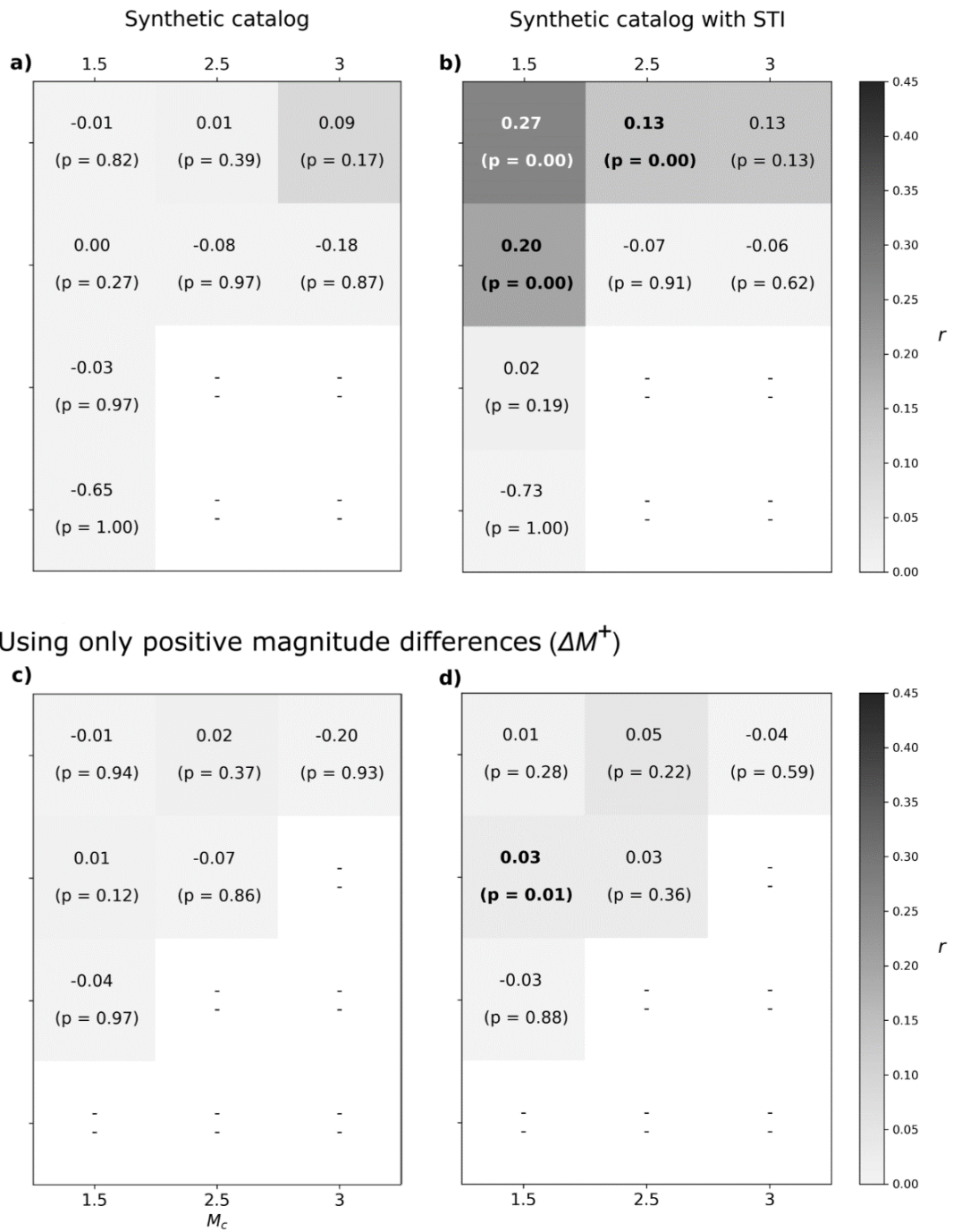
**Figure 9.6** Investigating magnitude correlation in the real and synthetic catalog (post-STI period) using the Spearman correlation coefficient.



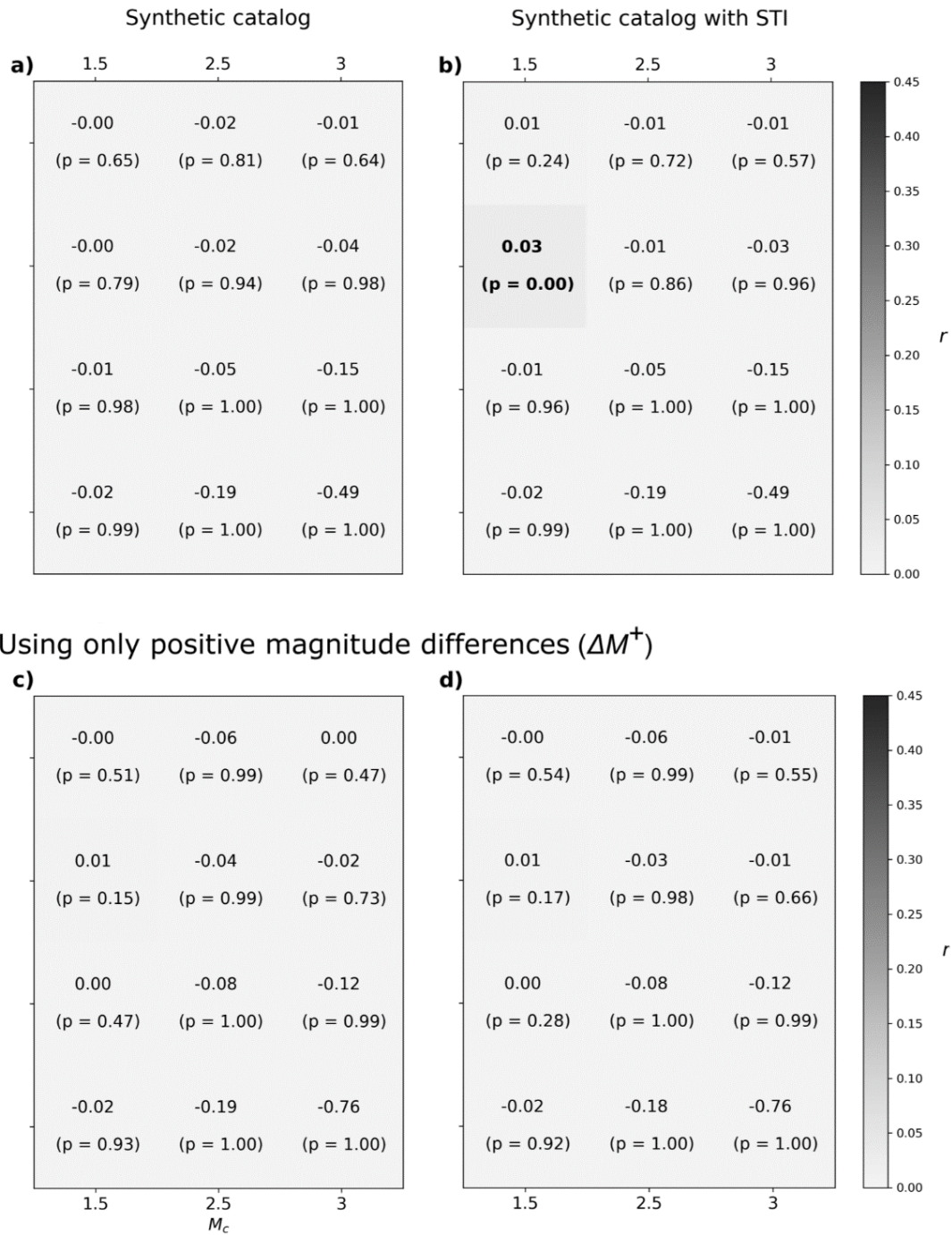
**Figure 9.7** Comparison of the timelines of the 2019 Ridgecrest foreshock sequence (red), with a zoom on the intense period 30 minutes before the first large earthquake of the Ridgecrest sequence ( $M_w$  6.4), with the complete (gray) and incomplete (black) synthetic sequence.



**Figure 9.8** Investigating STI following mainshocks in the incomplete synthetic catalog.



**Figure 9.9** Investigating magnitude correlation in the synthetic catalog (with *K. Felzer's ETAS model*) in the STI period.



**Figure 9.10** Investigating magnitude correlation in the synthetic catalog (with K. Felzer's ETAS model) in the post-STI period.



# 10

## SUPPORTING INFORMATION FOR CHAPTER

### 3

This section is published as Supporting Information of

Piegari, E., Corrado, P., Herrmann, M., and Marzocchi, W. (2025). Structural heterogeneities and spatial variations of seismicity drive temporal *b*-value changes. *Geophysical Research Letters*.

## 10.1 Text 1

The criteria to select DBSCAN parameters followed recommendations from previous cluster analyses of earthquake sequences (Piegari, *et al.* 2022). Since the horizontal extent of the central Italy sequence is significantly larger than its vertical extent, density-connected clusters of hypocenters primarily extend horizontally. However, DBSCAN's  $\varepsilon$ , i.e. the threshold for the neighboring distance, implies an isotropic kernel that would not acknowledge the anisotropic seismicity distribution. To make DBSCAN clustering more effective in this case, we rescaled the hypocenter coordinates to achieve uniform scaling in all directions: we normalized them with a min-max transformation, effectively transforming the data into a cube of edge length 12 km. This adjustment increased the local density of hypocenters in horizontal planes, making it easier to identify clusters with horizontally elongated shapes. We then applied DBSCAN using parameter values reported in Table [10.1](#). These configurations resulted in nine clusters during Period I, three clusters in Period II, nine clusters in Period III and seven clusters in Period IV. In each period, we selected only the closest clusters to the Norcia mainshock and named them “Norcia cluster”. We observe that the Norcia cluster in Periods I and II coincides with the largest cluster.

## 10.2 Text 2

To determine if a three-dimensional cluster of hypocenters is associated with a planar feature, we perform a principal component analysis (PCA). PCA

diagonalizes the covariance matrix to find a new coordinate basis that maximizes data variation from the mean, yielding three eigenvectors  $u_1$ ,  $u_2$  and  $u_3$ , which are orthonormal to each other. The three associated eigenvalues  $\lambda_1$ ,  $\lambda_2$ ,  $\lambda_3$  represent the variance in this new uncorrelated reference system.

Following Ouillon *et al.* (2008), the cluster can be approximated by a plane if the two largest eigenvalues  $\lambda_1$  and  $\lambda_2$  are significantly larger than  $\lambda_3$ —in this study at least two times larger. The orientation of the plane is characterized by the three eigenvectors. The dimensions (length  $L$  and height  $H$ ) depend on  $\lambda_1$  and  $\lambda_2$  expressed as  $\sqrt{\lambda_1}$  and  $\sqrt{\lambda_2}$ , assuming that hypocenter locations are uniformly distributed over the planes (Ouillon, *et al.* 2008). The strike (azimuth of a horizontal line on the plane) and dip (angle of maximum inclination of the plane) angles are computed as described by Quinn and Ehlmann (Quinn and Ehlmann 2019):

$$\text{strike} = \tan^{-1} \frac{u_{31}}{u_{32}} - \frac{\pi}{2} \quad (10.1)$$

$$\text{dip} = \cos^{-1} \frac{u_{33}}{\|u_3\|} \quad (10.2)$$

where  $u_{31}$ ,  $u_{32}$  and  $u_{33}$  are the components of  $u_3$ .

In Period I, we applied PCA to the five subclusters within the Norcia cluster obtained from the second-order DBSCAN analysis (see “[Results](#)” in the main text). The values of  $\lambda_1$ ,  $\lambda_2$ , and  $\lambda_3$  for each cluster are reported in Table [10.2](#). The condition for dimensionality reduction is satisfied only for clusters C1 and C5, both characterized by high dip angles. However, since C5 is much smaller than

C1, containing approximately one-third of the events of C1 (see Table [10.2](#)), we have decided to neglect it in the subsequent analyses. In Period II, we applied PCA to the entire Norcia cluster.

### 10.3 Text 3

To assess how subcluster selection in Period I influences fault plane identification, we performed an additional analysis with two different choices based on the OPTICS reachability plot (see Figure [3.2a](#) and “[Data and Methods](#)”). We determined the local maxima of the reachability distance (with MATLAB's “findpeaks” function), highlighting those with a prominence of at least 200 m (shown in Figure [10.3](#), left hand side). We first applied PCA to a subcluster that spans from the start (position 1) to the first identified peak at position 533 (i.e., 533 events; which includes C5 and C2 in Figure [3.2a,c](#)), and obtained plane V1 with a dip of  $61.5^\circ$ , a strike of  $-17.4^\circ$ ,  $L = 4.99$  km, and  $H = 1.93$  km. Expanding this subcluster by adding events until the second peak at position 1076 (now including C1 in Figure [3.2a](#)), PCA revealed plane V2 with a dip of  $49.3^\circ$ , a strike of  $-18.05^\circ$ ,  $L = 7.11$  km, and  $H = 3.06$  km. These two high-angle planes are shown in the right-hand side of Figure [10.3](#). These planes influence the subsets created in Period III since the hypocenters are associated by their proximity to these planes. Accordingly, they affect the  $b$ -value in this period unnoticeably (Figure [10.4](#)).

#### 10.4 Text 4

I associate earthquakes in Period III with one of the two planes identified in the first and second periods, V and H, based on their proximity. Here, we consider the two alternative planes, V1 and V2, (see [Text 3](#)) instead of plane V (associated with cluster C1, see [Figure 3.2a,c](#)) and repeat the analysis in the main text in terms of  $b$ -value and KS-test. As reported in [Figure 10.4](#) and [Table 10.3](#), the results do not change noticeably compared to using plane V. This confirms the scenario that Period I is characterized by a fragmented structure, whose associated seismicity has similar behavior before and after the mainshock and is dissimilar to that associated with plane H.

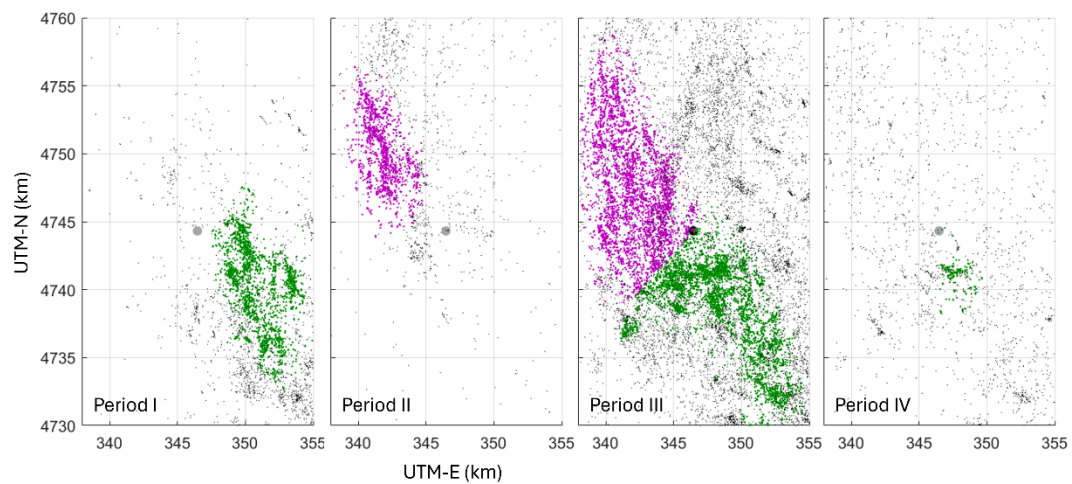
#### 10.5 Text 5

The identified V- and H- type structures are also recognizable in the study by Tan *et al.* (2021). Specifically in their [figure 3.3d](#), the earthquakes in green (corresponding to period II) below 5 km depth align well with my H-type homogenous structure ( $C^H$ , [Figure 3.2f](#)). In their [figure 3.4b](#) and [figure 3.4f](#), this structure is also at least partially recognizable during period III (as magenta/blue below 5km). The V-type fragmented structure instead is outlined by a dashed ellipse in their [Figures 3.3f](#) and [3.4f](#) for period I and period III, respectively.

To better visualize the retrieved structures in Period I, [Figure 10.7](#) shows the spatial seismicity distribution of the events as in [Figure 3.2c](#) and [d](#) but using points of view perpendicular to the strike of the planes for subclusters C1 and C5, respectively (with the North axis aligned along the strike). We would like

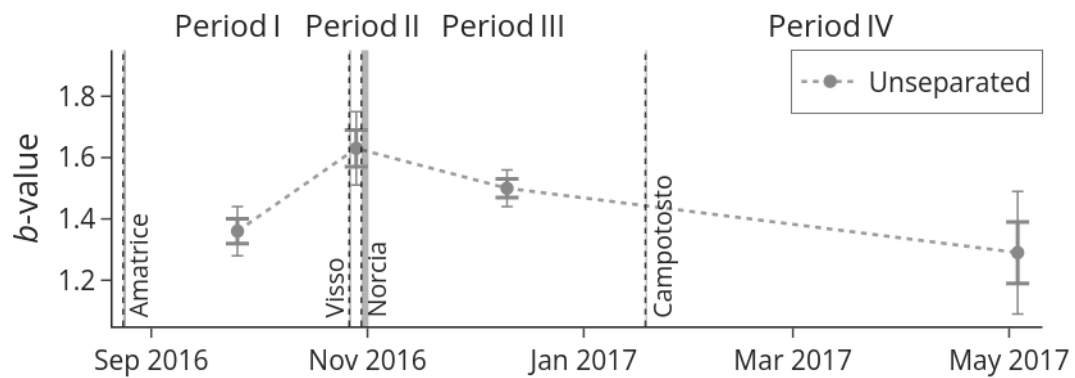
to specify that, although we show only sections of the clusters, all the events within the clusters—which are three-dimensional—are considered for the determination of the fault planes. This allows us to retain all the three-dimensional information that would be lost if only the projections along certain sections were considered.

Finally, we want to comment on the difference between my approach and that by Tan *et al.* (2021) in finding earthquake clusters. Tan *et al.* (2021) applied HDBSCAN, which, like DBSCAN, is very helpful for the automatic removal of data classified as noise, facilitating the identification of the highest-density volumes of earthquakes. Although HDBSCAN has the advantage of not requiring the selection of a single search radius for clustering data ( $\epsilon$ ), its stability-based cluster selection may not be the optimal for identifying (relatively small) multiple fault segments, if they do not form stable clusters that persist over a wide range of density thresholds and are instead classified as noise. For this reason, we prefer to use the reachability plot from OPTICS, which reveals the internal density structure in a more accessible way (e.g., valleys as nested denser clusters) and guide the selection of the DBSCAN neighborhood radius parameter ( $Z$ ), making it easier to control the level of detail and, consequently, the scale length at which the structure is reconstructed.

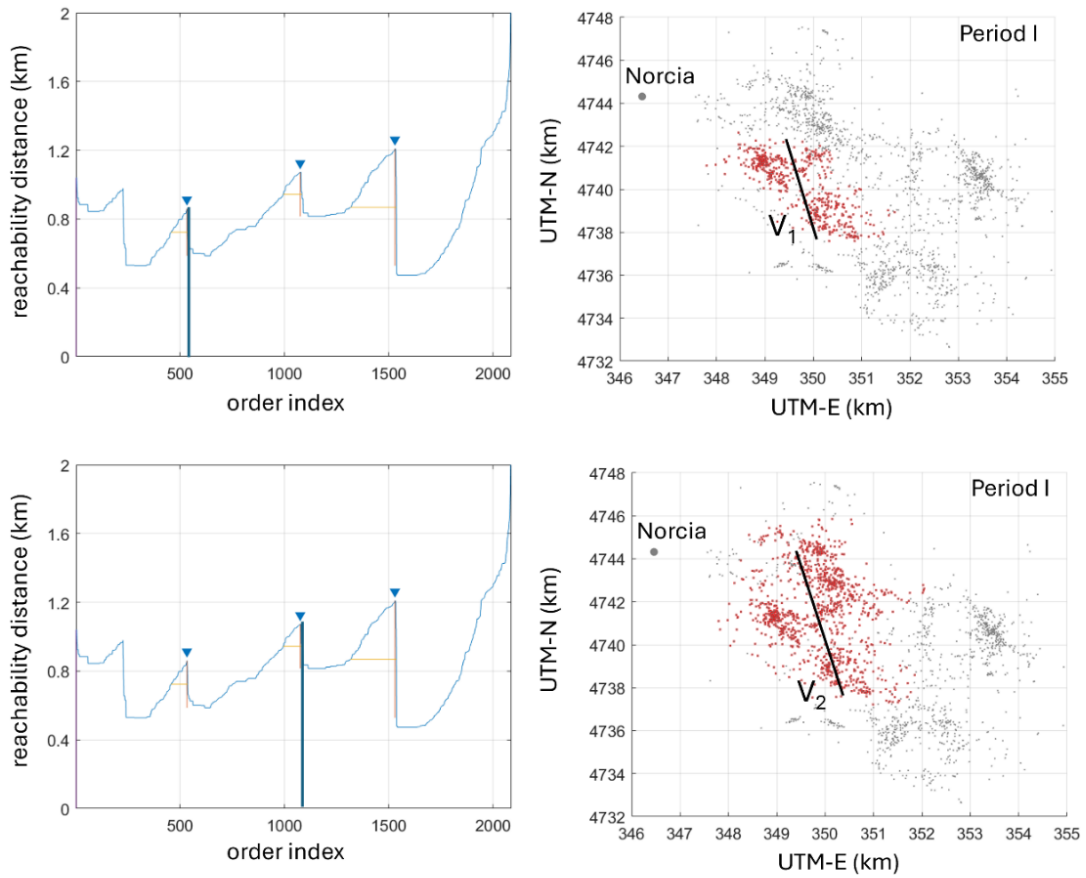


**Figure 10.1** Temporal evolution of the Norcia cluster.

The clusters and subset are highlighted clusters and subsets. These map views correspond to the depth sections in Figure 3.2e–h.

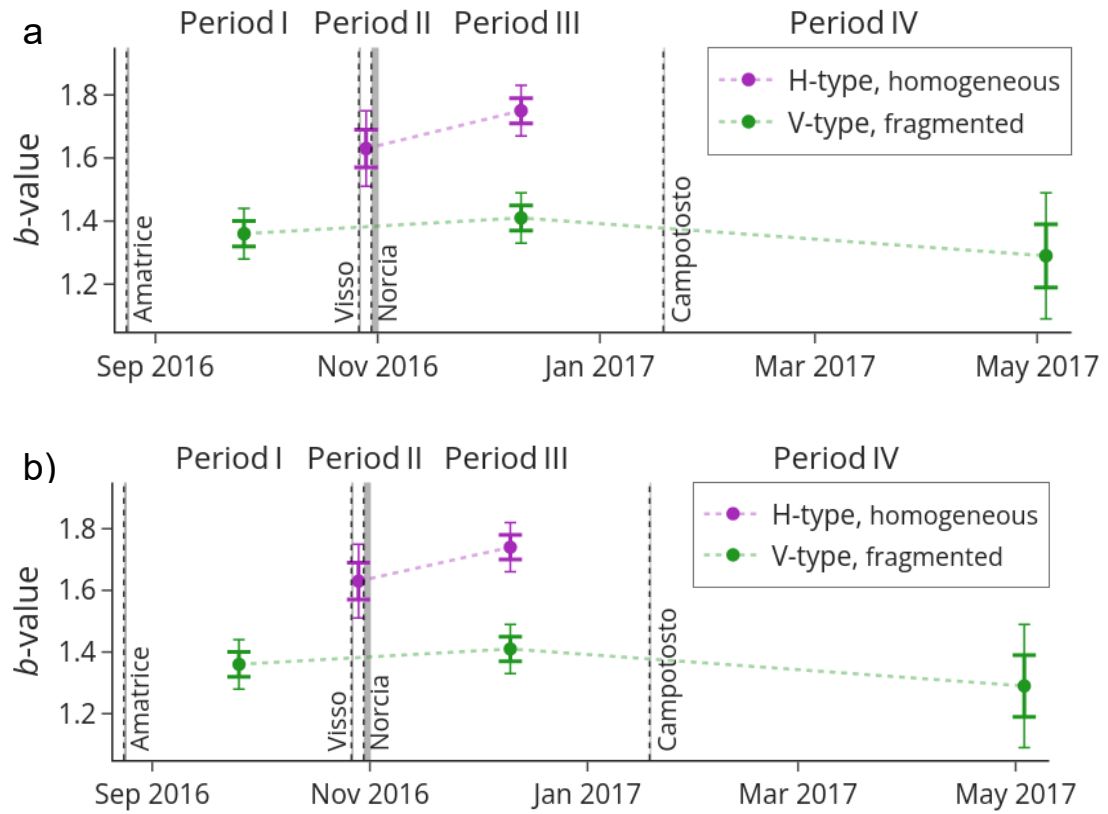


**Figure 10.2** Apparent  $b$ -value evolution if both  $V$ - and  $H$ - type structures are not treated separately.

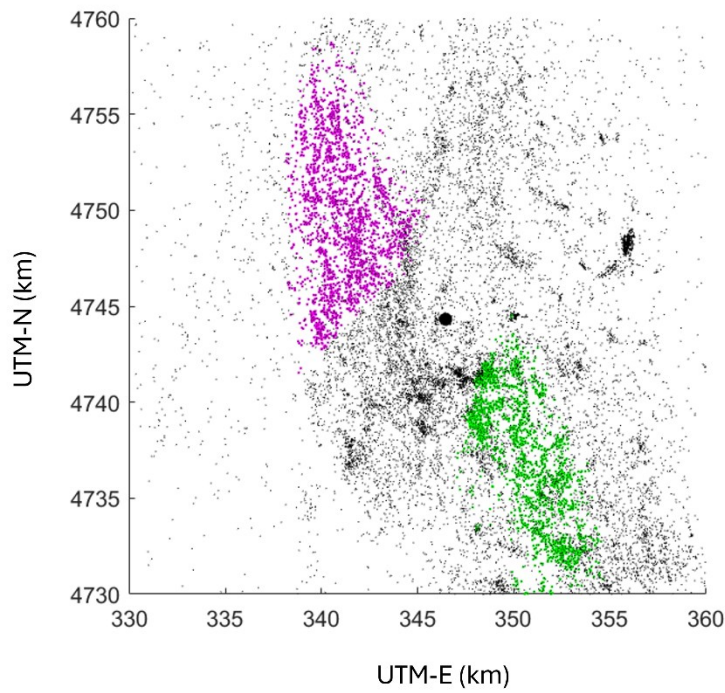


**Figure 10.3 Cluster identification from OPTICS reachability plots.**

On the left: reachability plots of the Norcia cluster (2'088 events) in Period I with indicated peaks used for cluster identification: dataset 1 (top) consisting of 533 events from the start (position 1) up to the first peak (position 533); dataset 2 (bottom) consisting of 1'076 events from the start up to the second peak (position 1076). On the right: map view of the Norcia cluster with highlighted dataset 1 (top) and dataset 2 (bottom) in red; black lines indicate the vertical planes  $V_1$  and  $V_2$  derived from PCA.

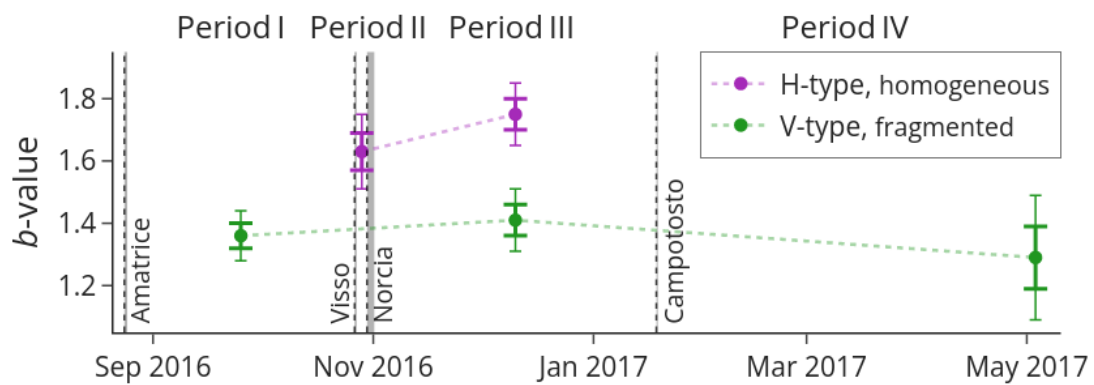


**Figure 10.4** Temporal  $b$ -value evolution using a different set of planes: a) V1 and H, b) V2 and H.

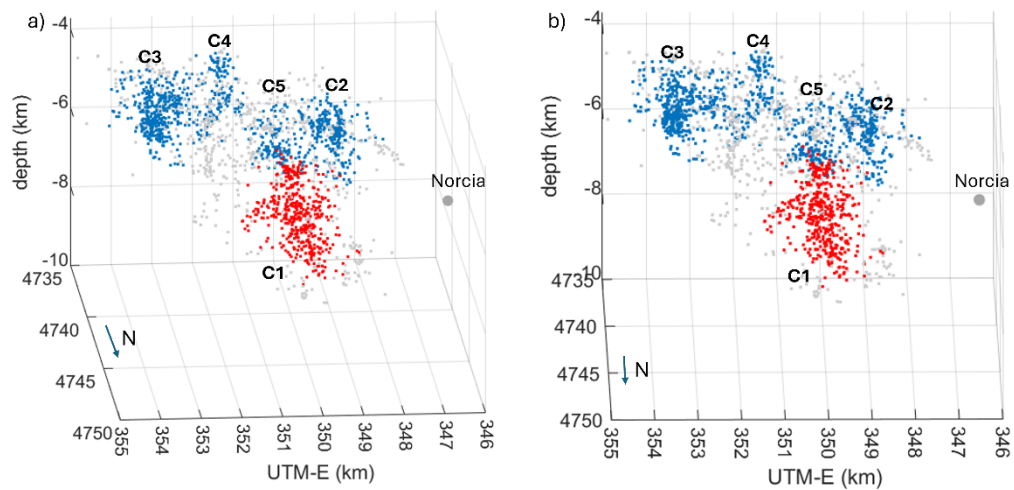


**Figure 10.5** *Norcia cluster in Period III with highlighted clusters excluding a 5 km buffer zone.*

*The black dot indicates the Norcia mainshock.*



**Figure 10.6** *Temporal  $b$ -value evolution using spatially more confined subsets excluding a 5 km buffer zone.*



**Figure 10.7** Map-view and depth section of the five subclusters showing viewpoints perpendicular to the strike of the retrieved planes for subclusters C1 and C5.

**Table 10.1** DBSCAN input parameters and characteristics of the Norcia cluster across the four periods.

| Temporal periods | Input parameters   |     | Characteristics of the Norcia cluster |                        |                    |          |
|------------------|--------------------|-----|---------------------------------------|------------------------|--------------------|----------|
|                  | $\varepsilon$ (km) | $Z$ | min-max UTM-E (km)                    | min-max UTM-N (km)     | min-max depth (km) | # events |
| Period I         | 0.4                | 100 | 347.5691<br>355.5007                  | 4732.6464<br>4747.5383 | -8.008<br>-3.7320  | 2088     |
| Period II        | 0.4                | 100 | 338.8637<br>345.0823                  | 4743.872<br>4756.7856  | -8.2900<br>-5.6610 | 1269     |
| Period III       | 0.4                | 160 | 338.1568<br>354.6321                  | 4728.456<br>4758.7270  | -9.0680<br>-4.7410 | 7487     |
| Period IV        | 0.4                | 100 | 346.5372<br>349.6352                  | 4738.281<br>4744.5410  | -6.2680<br>-5.2210 | 164      |

**Table 10.2 PCA eigenvalues and inferred fault plane parameters.**

| Time interval | cluster         | min-max depth (km) | # events | PCA eigenvalues       |                       |                       | Inferred fault plane parameters |            |        |        |
|---------------|-----------------|--------------------|----------|-----------------------|-----------------------|-----------------------|---------------------------------|------------|--------|--------|
|               |                 |                    |          | l1 (km <sup>2</sup> ) | l2 (km <sup>2</sup> ) | l3 (km <sup>2</sup> ) | Dip (°)                         | Strike (°) | L (km) | H (km) |
| Period I      | C1              | -8.008<br>-5.377   | 433      | 1.21                  | 0.24                  | 0.09                  | 63.3                            | -21.4      | 1.7    | 3.8    |
|               | C2              | -5.7780<br>-3.7640 | 324      | 0.49                  | 0.15                  | 0.10                  | -                               | -          | -      | -      |
|               | C3              | -6.3710<br>-4.2600 | 275      | 0.31                  | 0.23                  | 0.12                  | -                               | -          | -      | -      |
|               | C4              | -6.4880<br>-4.4500 | 210      | 0.36                  | 0.21                  | 0.12                  | -                               | -          | -      | -      |
|               | C5              | -6.7230<br>-5.0100 | 126      | 0.25                  | 0.15                  | 0.07                  | 87.5                            | -3.7       | 1.3    | 1.7    |
| Period II     | C <sup>II</sup> | -8.2900<br>-5.6610 | 1269     | 6.58                  | 0.97                  | 0.15                  | 8.4                             | -136.2     | 8.9    | 3.4    |

**Table 10.3 b-positive values for the two structures across periods.**

|            | C <sup>I</sup> | C <sup>II</sup> | S <sub>III</sub> <sup>V</sup> | S <sub>III</sub> <sup>H</sup> | C <sup>IV</sup> |
|------------|----------------|-----------------|-------------------------------|-------------------------------|-----------------|
| b-positive | 1.30±0.04      | 1.62±0.07       | 1.39±0.03                     | 1.59±0.04                     | 1.47±0.16       |

**Table 10.4 p-values from the KS test including the remaining pairs.**

That is, adding the last three rows to report p-values of the two-sample Kolmogorov–Smirnov test between every cluster.

|                               | C <sup>I</sup>       | C <sup>II</sup>      | S <sub>III</sub> <sup>V</sup> | S <sub>III</sub> <sup>H</sup> | C <sup>IV</sup>      |
|-------------------------------|----------------------|----------------------|-------------------------------|-------------------------------|----------------------|
| C <sup>I</sup>                | -                    | 5.0*10 <sup>-3</sup> | 0.82                          | 6.0*10 <sup>-4</sup>          | 0.46                 |
| C <sup>II</sup>               | 5.0*10 <sup>-3</sup> | -                    | 0.01                          | 0.10                          | 0.04                 |
| S <sub>III</sub> <sup>V</sup> | 0.42                 | 0.01                 | -                             | 1.0*10 <sup>-4</sup>          | 0.18                 |
| S <sub>III</sub> <sup>H</sup> | 4.0*10 <sup>-5</sup> | 0.10                 | 1.0*10 <sup>-4</sup>          | -                             | 5.0*10 <sup>-3</sup> |
| C <sup>IV</sup>               | 0.46                 | 0.04                 | 0.18                          | 5.0*10 <sup>-3</sup>          | -                    |

**Table 10.5 p-values from the KS test using different subsets in Period III, which are associated with the set of planes V1 and H.**

|                               | C <sup>I</sup>       | C <sup>II</sup>      | S <sub>III</sub> <sup>V</sup> | S <sub>III</sub> <sup>H</sup> | C <sup>IV</sup>      |
|-------------------------------|----------------------|----------------------|-------------------------------|-------------------------------|----------------------|
| C <sup>I</sup>                | -                    | 5.0*10 <sup>-3</sup> | 0.82                          | 6.0*10 <sup>-4</sup>          | 0.46                 |
| C <sup>II</sup>               | 5.0*10 <sup>-3</sup> | -                    | 0.01                          | 0.24                          | 0.04                 |
| S <sub>III</sub> <sup>V</sup> | 0.82                 | 0.01                 | -                             | 9.0*10 <sup>-4</sup>          | 0.18                 |
| S <sub>III</sub> <sup>H</sup> | 4.0*10 <sup>-5</sup> | 0.10                 | 9.0*10 <sup>-4</sup>          | -                             | 2.0*10 <sup>-2</sup> |
| C <sup>IV</sup>               | 0.46                 | 0.04                 | 0.18                          | 2.0*10 <sup>-2</sup>          | -                    |

**Table 10.6** *p-values of the KS test using different subsets in Period III, which are associated with the set of planes V2 and H.*

|             | $C^I$               | $C^{II}$            | $S_{III}^V$         | $S_{III}^H$         | $C^{IV}$            |
|-------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| $C^I$       | -                   | $5.0 \cdot 10^{-3}$ | 0.80                | $4.0 \cdot 10^{-4}$ | 0.46                |
| $C^{II}$    | $5.0 \cdot 10^{-3}$ | -                   | $9.0 \cdot 10^{-3}$ | 0.20                | 0.04                |
| $S_{III}^V$ | 0.80                | $9.0 \cdot 10^{-3}$ | -                   | $4.0 \cdot 10^{-4}$ | 0.18                |
| $S_{III}^H$ | $4.0 \cdot 10^{-4}$ | 0.20                | $4.0 \cdot 10^{-4}$ | -                   | $2.0 \cdot 10^{-2}$ |
| $C^{IV}$    | 0.46                | 0.04                | 0.18                | $2.0 \cdot 10^{-2}$ | -                   |

**Table 10.7** *p-values of the KS test excluding a 5 km buffer zone.*

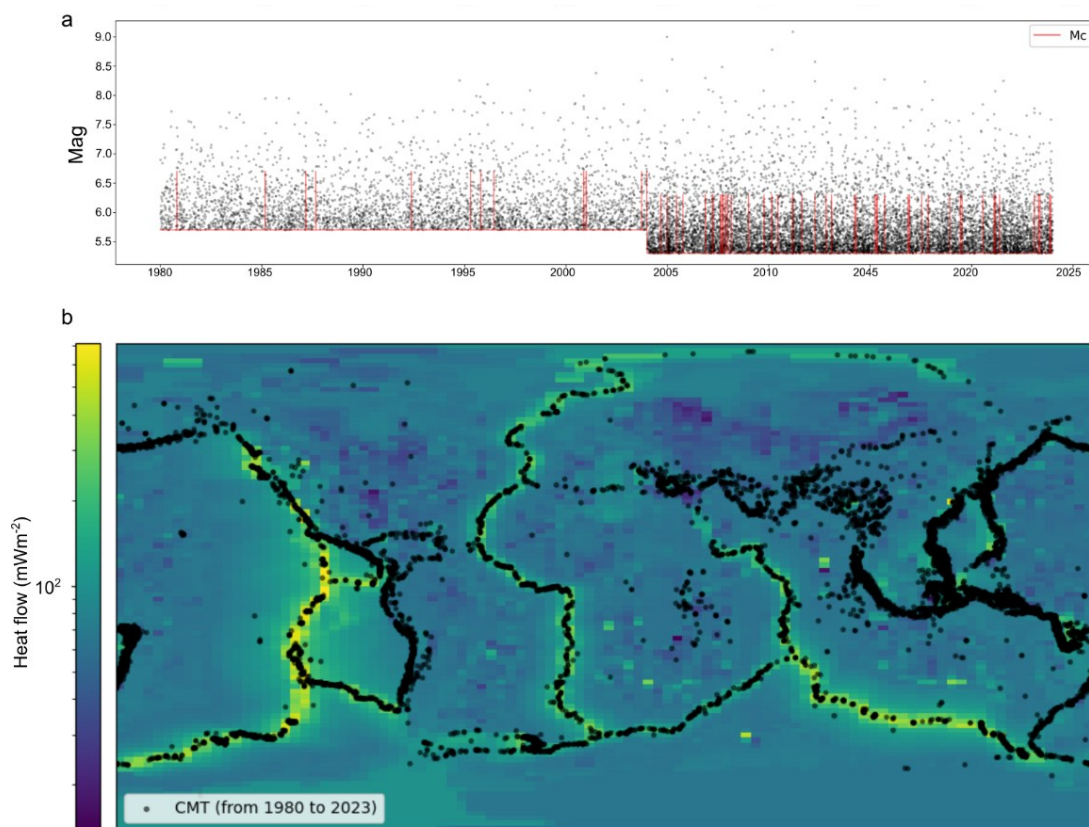
|          | $C^I$               | $C^{II}$            | $S_{III}^V$         | $S_{III}^H$         | $C^{IV}$ |
|----------|---------------------|---------------------|---------------------|---------------------|----------|
| $C^I$    | -                   | $5.0 \cdot 10^{-3}$ | 0.38                | $1.0 \cdot 10^{-4}$ | 0.46     |
| $C^{II}$ | $5.0 \cdot 10^{-3}$ | -                   | $6.0 \cdot 10^{-3}$ | 0.65                | 0.04     |



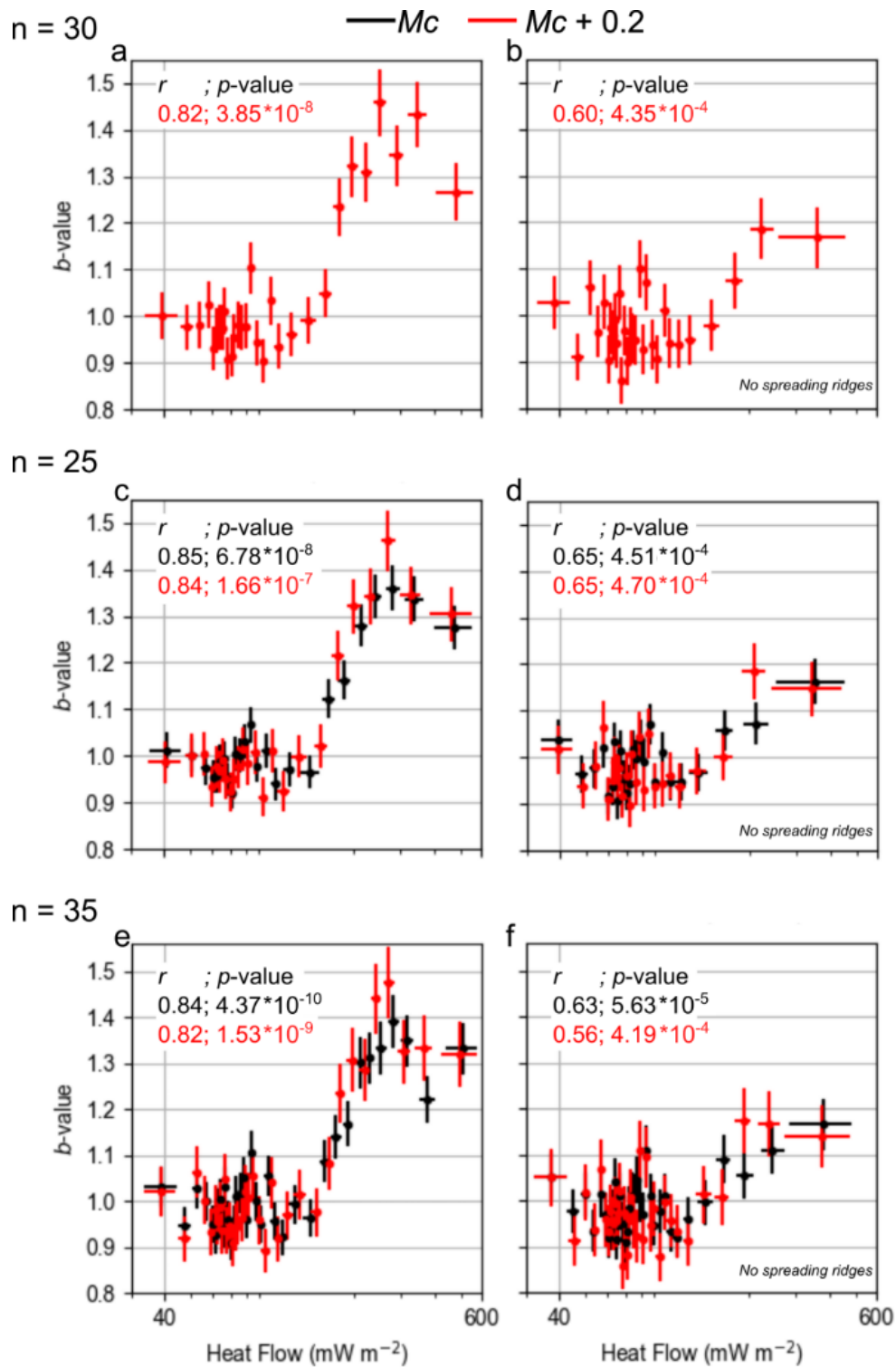
## 11

## SUPPORTING INFORMATION FOR CHAPTER

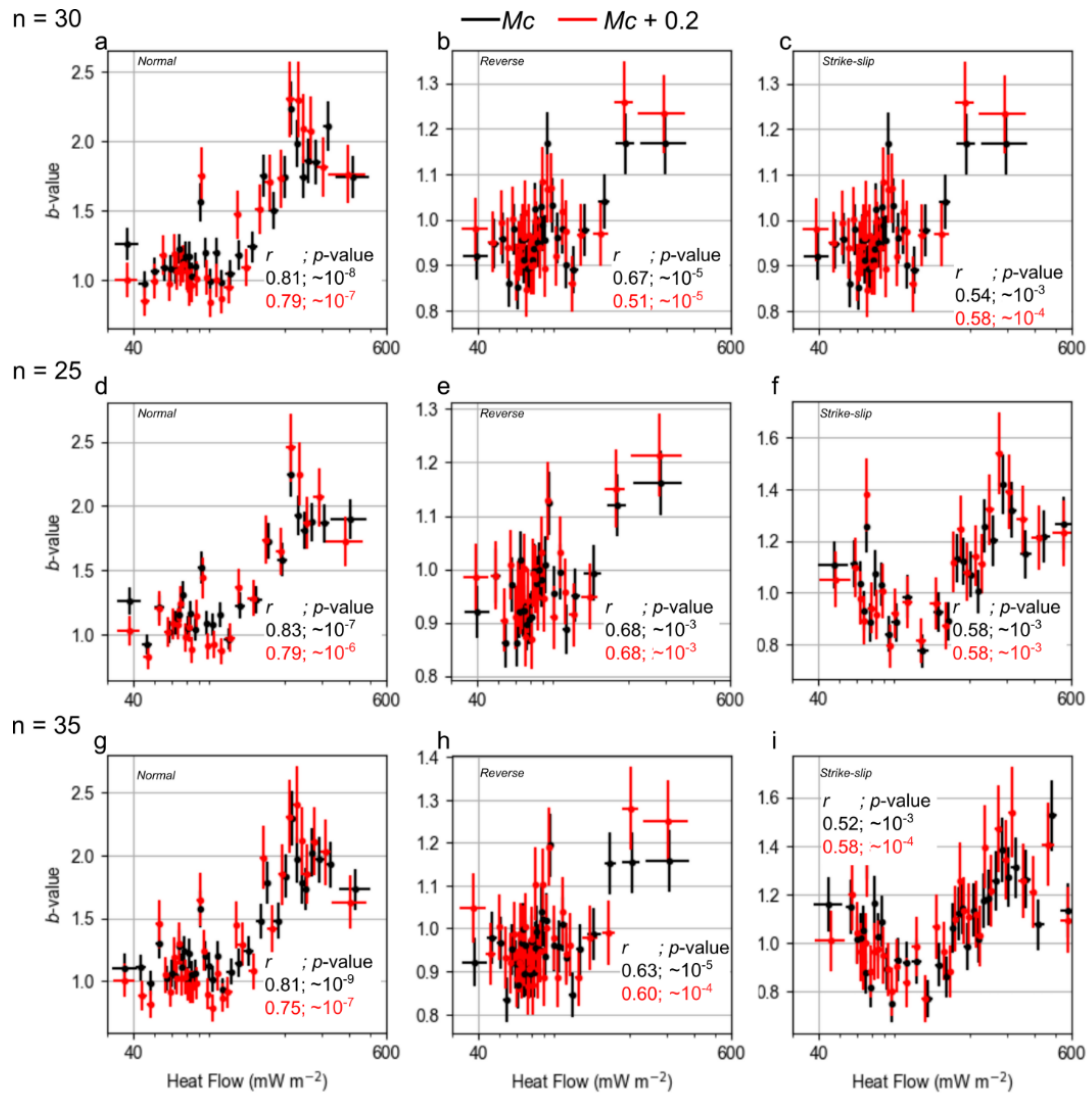
## 4



*Figure 11.1 Temporal and spatial distribution of the events using a more conservative completeness magnitude ( $M_c + 0.2$ ).*

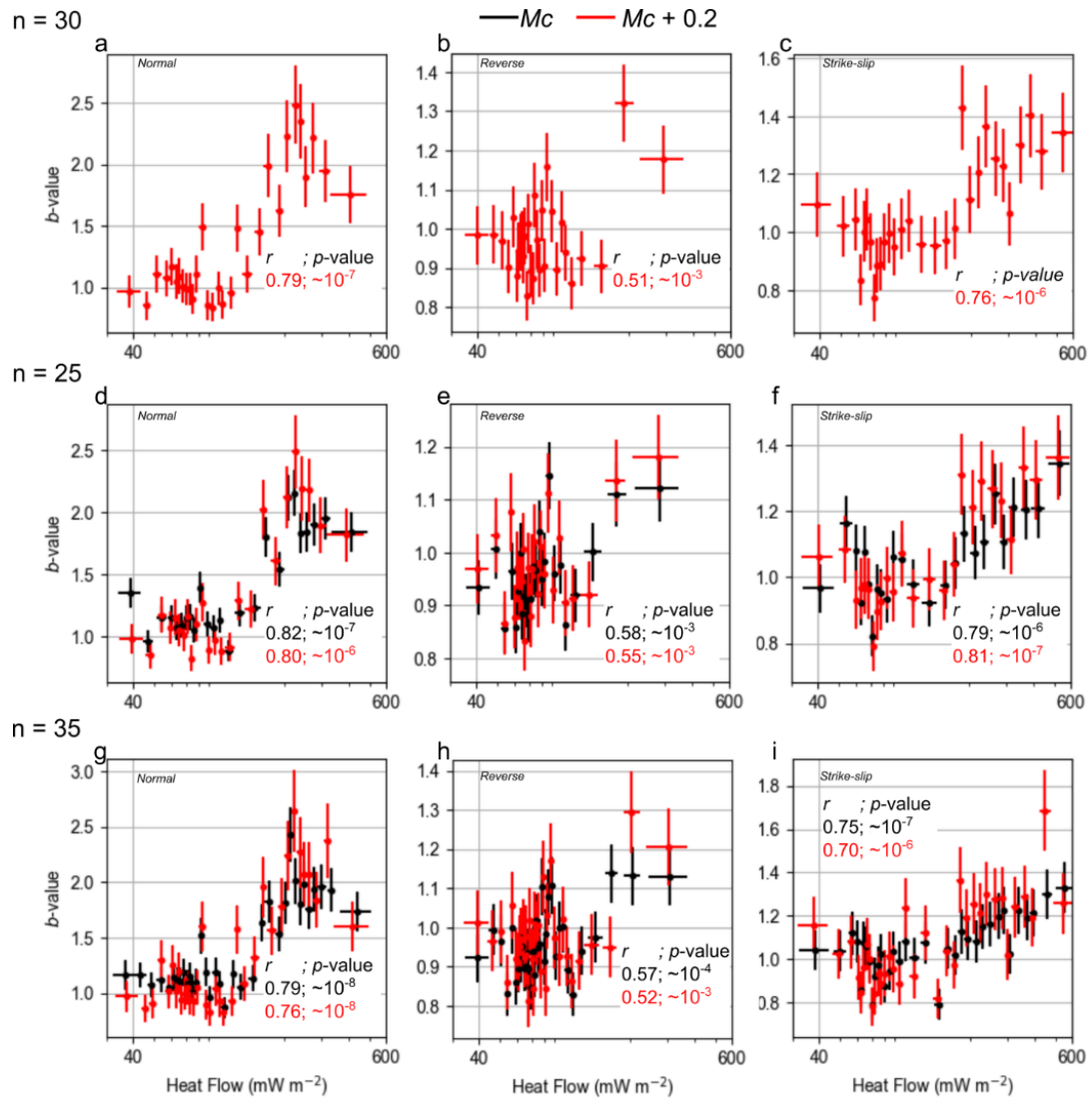


**Figure 11.2** Correlation between  $b$ -value and heat flow using a more conservative  $Mc$  and using different number of intervals. The Pearson correlation coefficients and their  $p$ -values are listed in the top-left corner of each panel.



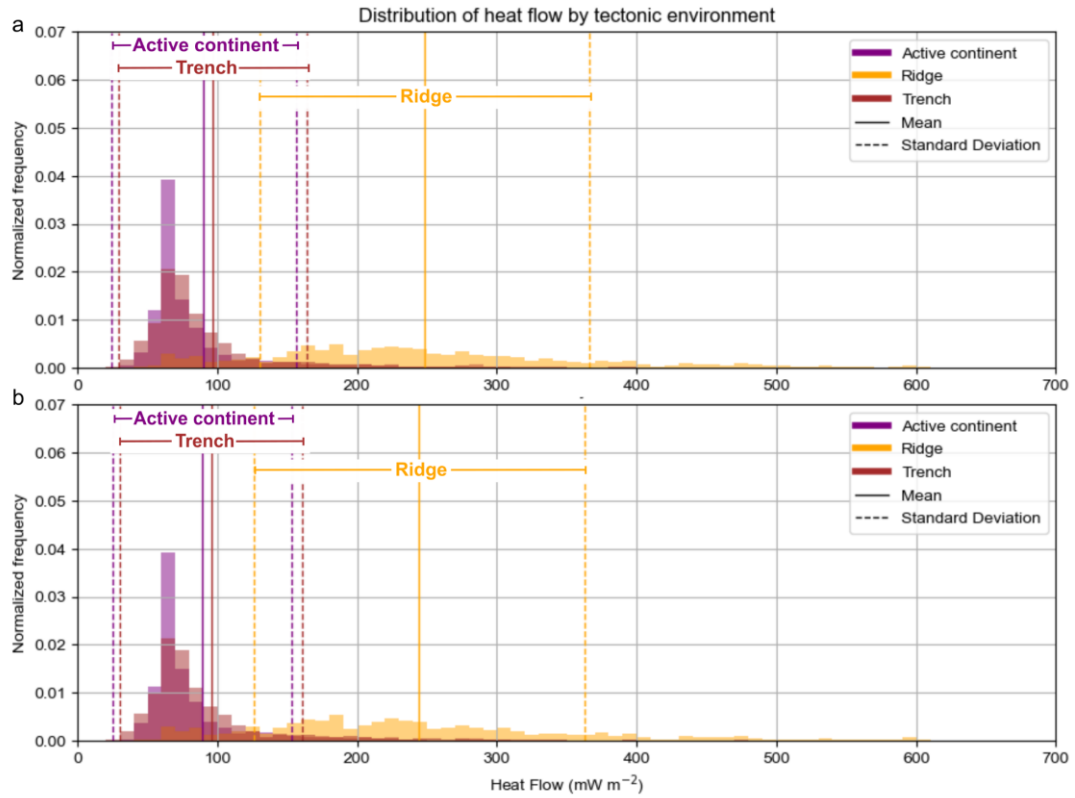
**Figure 11.3** Correlation between  $b$ -value and heat flow grouping the events according to the focal mechanism and using the second solution of the CMT, a more conservative  $Mc$  and using different number of intervals.

The Pearson correlation coefficients and their  $p$ -values are listed in each panel.

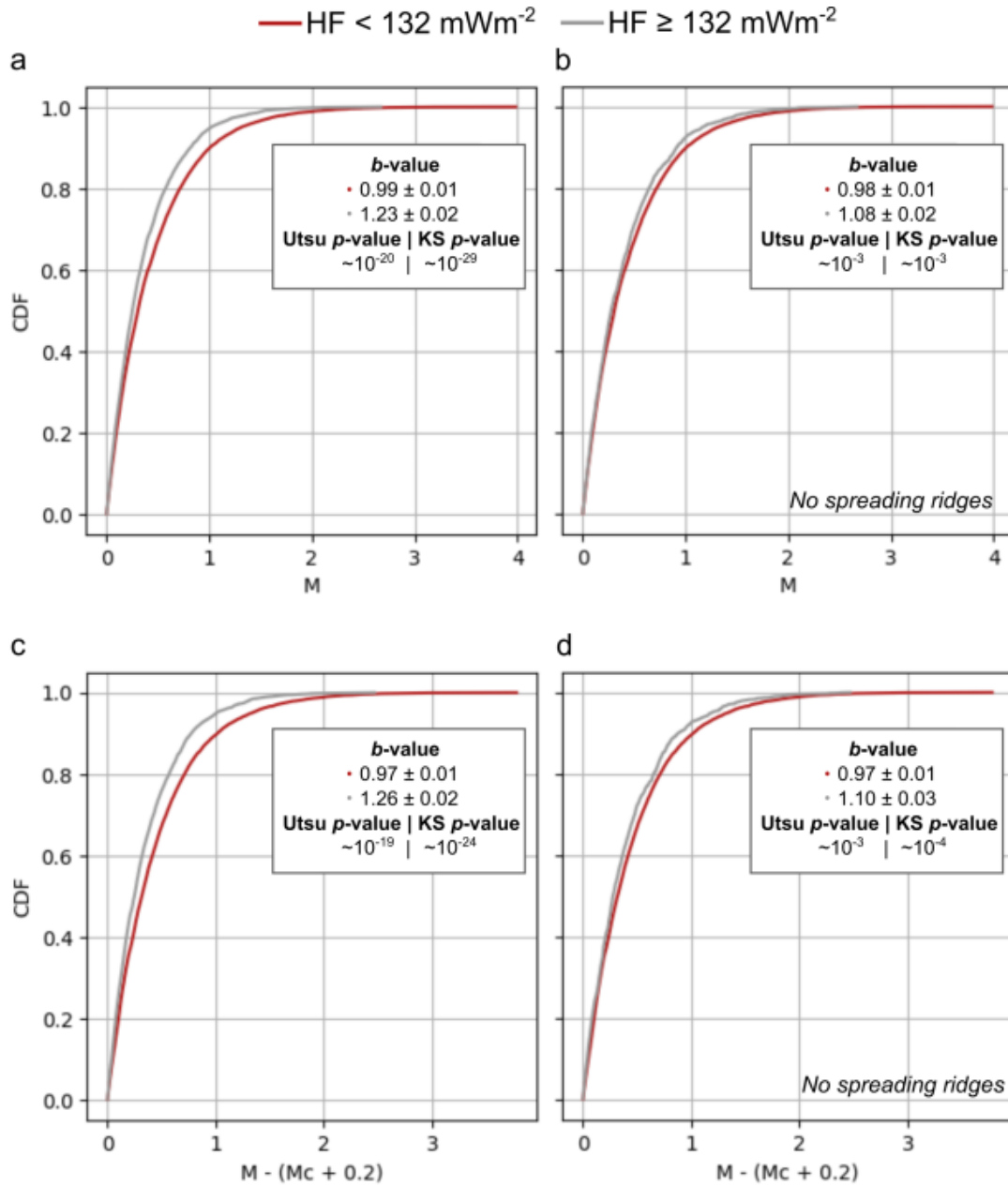


**Figure 11.4** Correlation between  $b$ -value and heat flow grouping the events according to the focal mechanism and using the first solution of the CMT, a more conservative  $Mc$  and using different number of intervals.

The Pearson correlation coefficients and their  $p$ -values are listed in each panel.

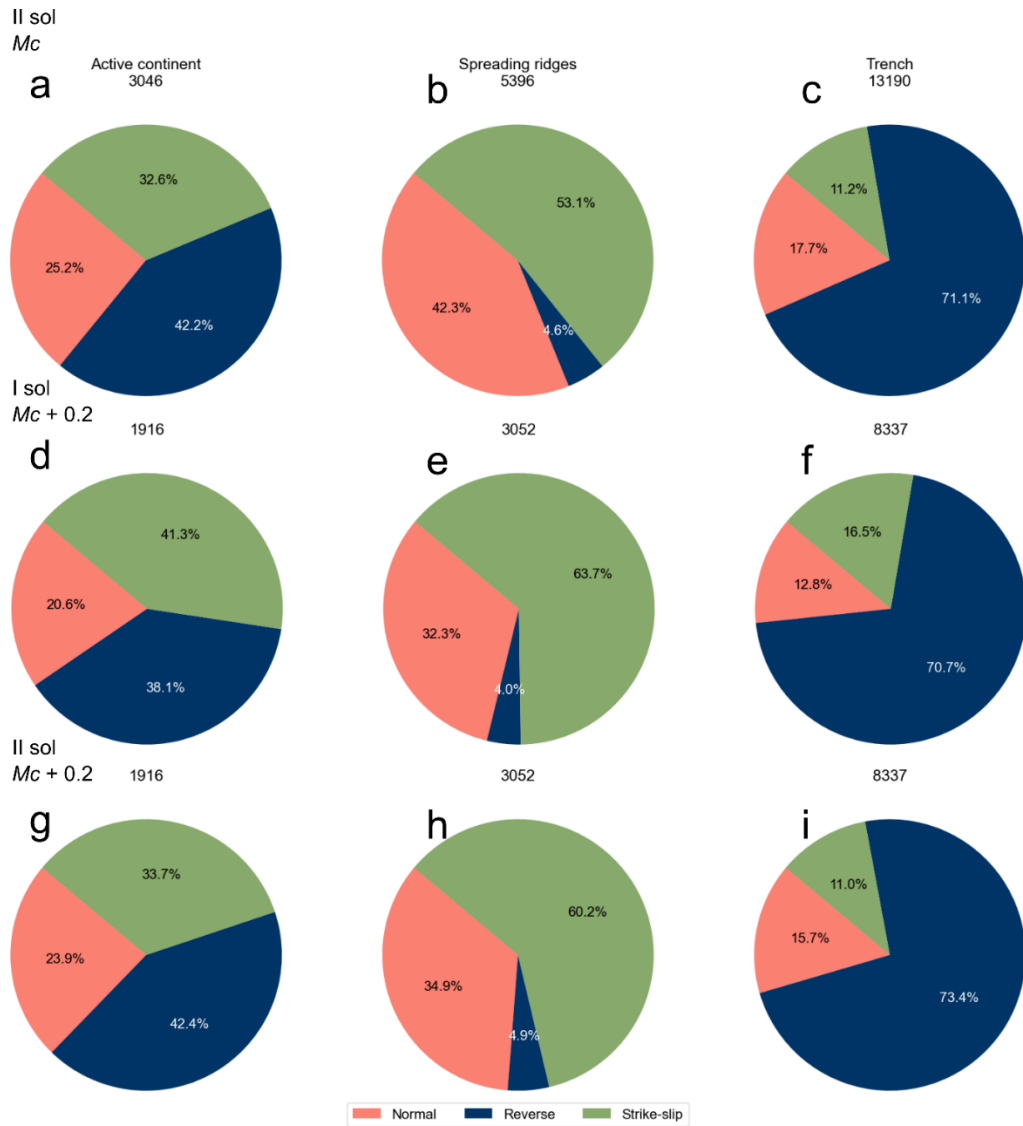


*Figure 11.5 Distribution of the heat flow in the three main tectonic zones considering only the events above the  $M_C$  (a) and above  $M_C + 0.2$  (b).*



**Figure 11.6 Cumulative distributions of the magnitudes.**

CDF below  $132 \text{ mWm}^{-2}$  are in red and above are in gray. a-c) All the events; b-d) Excluding events occurred in spreading ridges. c-d) using a more conservative estimation of  $M_c$ . On the top-right corner are listed: the  $b$ -values; the  $p$ -value of the Utsu test (Utsu, 1999) between the  $b$ -values; the  $p$ -value of the two-samples Kolmogorov-Smirnov test (Gibbons and Chakraborti, 2003) between the magnitude distributions.



*Figure 11.7 Percentages of occurrence of normal, reverse and strike-slip events in each tectonic environment using a more conservative estimation of the  $M_c$  and the second solution of the CMT.*

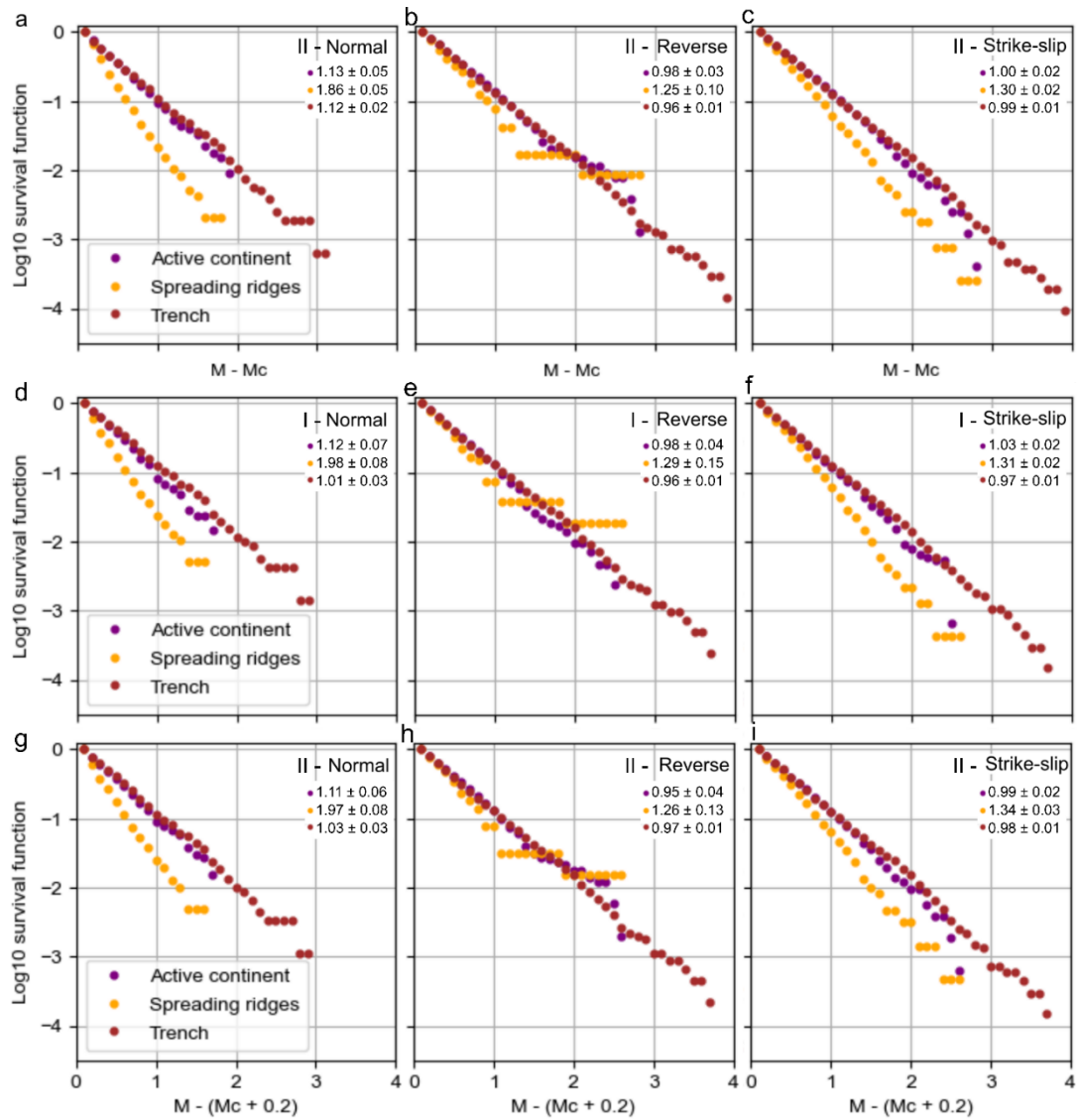
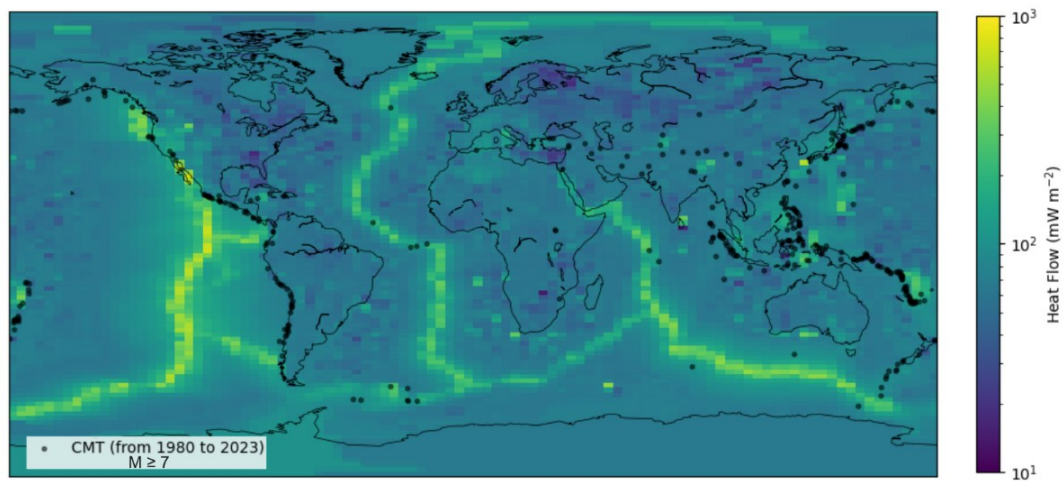


Figure 11.8 MFD for each focal mechanism grouping according to the tectonic environment using the second solution of the CMT and using a more conservative estimation of  $M_c$ .



*Figure 11.9 Location of the latest major events (from 1900, magnitude greater than 7) with respect to the heat flow.*

**Table 11.1** Confirmatory results using an increased  $M_C$  of 1.5 in the 48 hours after a  $M7+$ .

| Pearson correlation    |                         | $r$                                                        | $p$ -value              |
|------------------------|-------------------------|------------------------------------------------------------|-------------------------|
| 30 intervals           | All                     | 0.84                                                       | $10^{-9}$               |
|                        | No spreading ridges     | 0.62                                                       | 0.0003                  |
|                        | Normal (I/II sol)       | 0.79/0.82                                                  | $10^{-7}/10^{-8}$       |
|                        | Reverse (I/II sol)      | 0.51/0.67                                                  | $0.004/10^{-5}$         |
|                        | Strike-slip (I/II sol)  | 0.75/0.54                                                  | $10^{-6}/0.002$         |
|                        |                         |                                                            |                         |
| $b$ -values            | Active continent        | Spreading ridges                                           | Trench                  |
| Normal (I/II sol)      | 1.12±0.05/<br>1.12±0.05 | 1.84±0.05/<br>1.86±0.05                                    | 1.12±0.03/<br>1.12±0.03 |
| Reverse (I/II sol)     | 1.00±0.04/<br>0.98±0.03 | 1.25±0.11/<br>1.23±0.10                                    | 0.95±0.01/<br>0.96±0.01 |
| Strike-slip (I/II sol) | 1.01±0.04/<br>0.98±0.04 | 1.15±0.03/<br>1.15±0.03                                    | 0.98±0.02/<br>0.98±0.03 |
|                        |                         |                                                            |                         |
| MW47                   |                         | $p$ -value<br>$<<10^{-10}$<br>$<<10^{-10}$<br>$<<10^{-10}$ |                         |
| AC <i>vs</i> R         |                         |                                                            |                         |
| AC <i>vs</i> T         |                         |                                                            |                         |
| R <i>vs</i> T          |                         |                                                            |                         |
|                        |                         |                                                            |                         |
|                        | All                     | No spreading ridges                                        |                         |
| Low HF ( $b$ -value)   | 0.99±0.01               | 0.98±0.01                                                  |                         |
| High HF ( $b$ -value)  | 1.23±0.02               | 1.09±0.02                                                  |                         |
| Utsu $p$ -value        | $<<10^{-10}$            | $10^{-6}$                                                  |                         |
| KS $p$ -value          | $<<10^{-10}$            | 0.0004                                                     |                         |

**Table 11.2** *Confirmatory results using only events characterized by a heat flow value under the median.*

| Pearson correlation    |                         | $r$                                                           | $p$ -value              |
|------------------------|-------------------------|---------------------------------------------------------------|-------------------------|
| 30 intervals           | All                     | 0.75                                                          | $10^{-6}$               |
|                        | No spreading ridges     | 0.50                                                          | 0.005                   |
|                        | Normal (I/II sol)       | 0.69/0.68                                                     | $10^{-5}/10^{-5}$       |
|                        | Reverse (I/II sol)      | 0.24/0.42                                                     | 0.19/0.02               |
|                        | Strike-slip (I/II sol)  | 0.75/0.63                                                     | $10^{-6}/0.0002$        |
|                        |                         |                                                               |                         |
| $b$ -values            | Active continent        | Spreading ridges                                              | Trench                  |
| Normal (I/II sol)      | 1.19±0.21/<br>1.05±0.17 | 1.85±0.05/<br>1.87±0.05                                       | 1.13±0.05/<br>1.14±0.04 |
| Reverse (I/II sol)     | 0.88±0.11/<br>0.83±0.10 | 1.38±0.15/<br>1.41±0.14                                       | 0.94±0.02/<br>0.95±0.02 |
| Strike-slip (I/II sol) | 0.94±0.10/<br>1.03±0.12 | 1.15±0.03/<br>1.16±0.03                                       | 0.94±0.04/<br>0.94±0.04 |
|                        |                         |                                                               |                         |
| MW47                   |                         | $p$ -value<br>$<<10^{-10}$<br>$\sim 10^{-10}$<br>$<<10^{-10}$ |                         |
| AC $vs$ R              |                         |                                                               |                         |
| AC $vs$ T              |                         |                                                               |                         |
| R $vs$ T               |                         |                                                               |                         |
|                        |                         |                                                               |                         |
|                        | All                     | No spreading ridges                                           |                         |
| Low HF ( $b$ -value)   | 0.96±0.02               | 0.95±0.02                                                     |                         |
| High HF ( $b$ -value)  | 1.27±0.02               | 1.06±0.03                                                     |                         |
| Utsu $p$ -value        | $<<10^{-10}$            | 0.049                                                         |                         |
| KS $p$ -value          | $<<10^{-10}$            | 0.0004                                                        |                         |

*Table 11.3  $p$ -values of the  $M_W$  statistical test between the heat flow distributions for events in different tectonic environments.*

|             |         | $p$ -value   |
|-------------|---------|--------------|
|             | AC vs R | $<<10^{-10}$ |
|             | AC vs T | $<<10^{-10}$ |
|             | R vs T  | $<<10^{-10}$ |
| $M_C + 0.2$ | AC vs R | $<<10^{-10}$ |
|             | AC vs T | $<<10^{-10}$ |
|             | R vs T  | $<<10^{-10}$ |



## 12

## SUPPORTING INFORMATION FOR CHAPTER

## 5

12.1 Estimation of the  $b$ -value with time-varying completeness

To estimate the GR  $b$ -value in the presence of a time-dependent completeness magnitude, I follow the procedure of Taroni (2021). The first step is the transformation of each observed magnitude  $M_i$  into the random variable

$$X_i = M_i - M_C(t_i), \quad (12.1)$$

where  $M_C(t_i)$  is the completeness magnitude valid at the time of the earthquake. This correction makes  $X_i$  exponentially distributed, thus allowing the use of the classical maximum-likelihood estimator of Aki (1965, equations 1.6-1.8).

This formulation is equivalent to the standard Aki (1965) estimator when  $M_C$  is constant but remains valid under variable completeness.

12.2 Joint estimation of the  $b$ -value and corner magnitude

For the simultaneous estimation of the  $b$ -value and the corner magnitude of the tapered GR distribution, I adopt the extended maximum-likelihood method

introduced by Taroni *et al.* (2021). In this framework, seismic moments are used instead of magnitudes, since the tapered Gutenberg–Richter distribution corresponds to a tapered Pareto distribution in moment space. The probability density function of the tapered Pareto distribution with variable completeness is

$$f^{(i)}(M_0) = \left( \frac{\beta}{M_0 + C_{M_0}} \right) \left( \frac{M_{0,min}^{(i)}}{M_0} \right)^\beta \exp \left( - \frac{M_{0,min}^{(i)} - M_0}{C_{M_0}} \right) \quad (12.3)$$

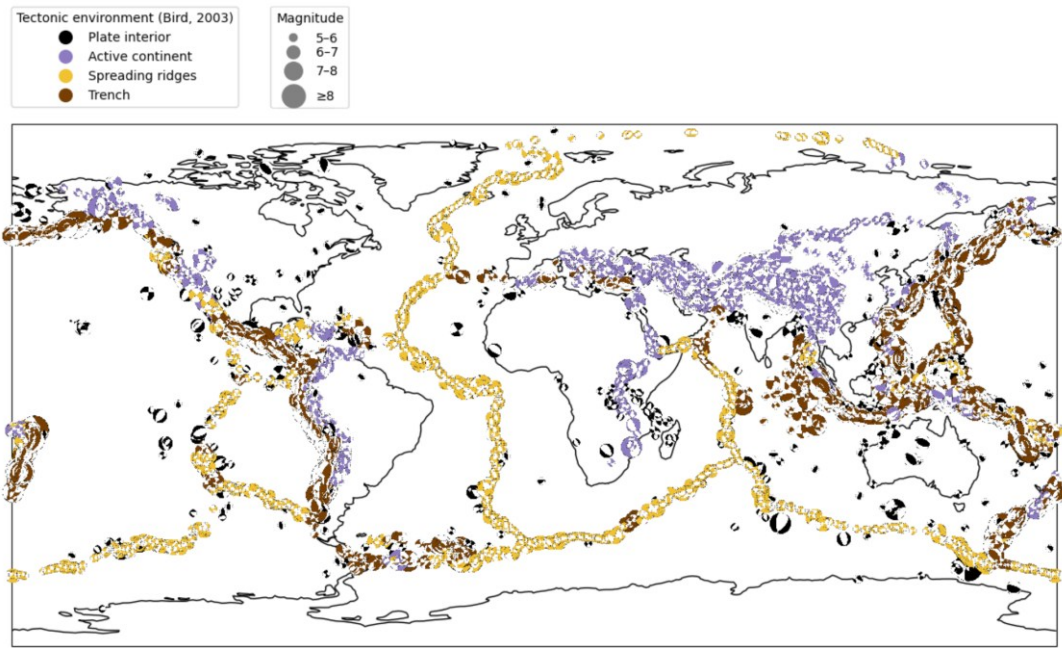
valid for  $M_{0,min}^{(i)} \leq M_0 < \infty$ , where  $\beta = \frac{2}{3}b$ ,  $M_{0,min}^{(i)}$  is the completeness moment at the time of the  $i$ -th event, and  $C_{M_0}$  is corner moment.

The joint-likelihood for a catalog of  $N$  events is obtained as

$$L(\beta, C_{M_0}) = \sum_{i=1}^N \ln[f^{(i)}(M_{0,i})], \quad (12.4)$$

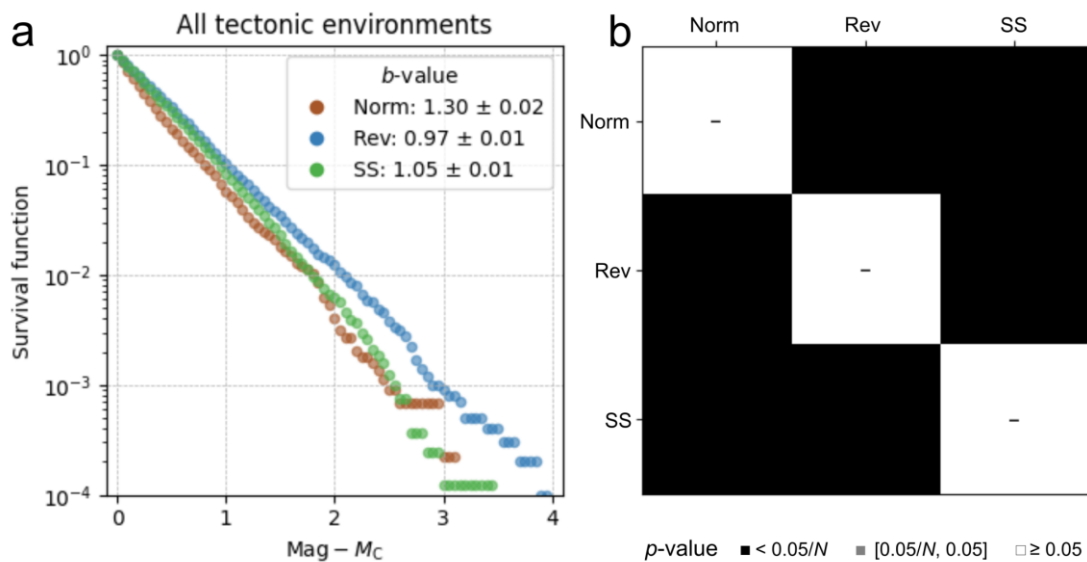
which is maximized over the parameter space to obtain the maximum-likelihood estimates of  $\beta$  and  $C_{M_0}$  (and thus the  $b$ -value and corner magnitude).

Uncertainties are quantified using the profile-likelihood method, i.e., cutting the log-likelihood surface at fixed thresholds and mapping the resulting confidence contours in the parameter space. This approach provides robust estimates and confidence regions without assuming a Poisson distribution of event occurrence and exploits the full dataset by incorporating multiple completeness levels.

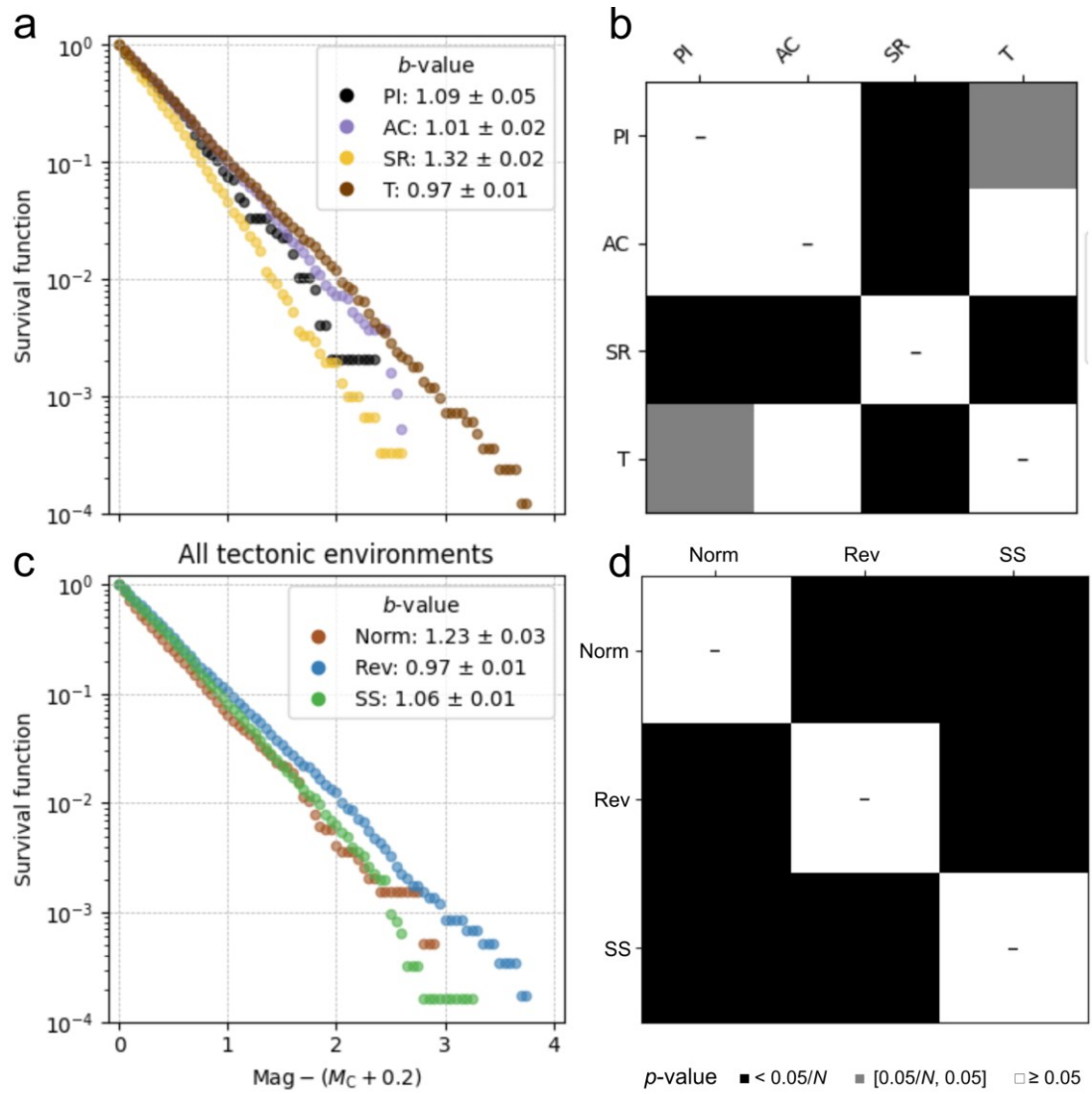


**Figure 12.1 Global distribution of focal mechanisms.**

The colors refer to the tectonic environment identified by Bird (2003): black = plate interior; purple = active continent; yellow = spreading ridges; brown = trench. The size of the “beach balls” is proportional to the magnitude of the event.

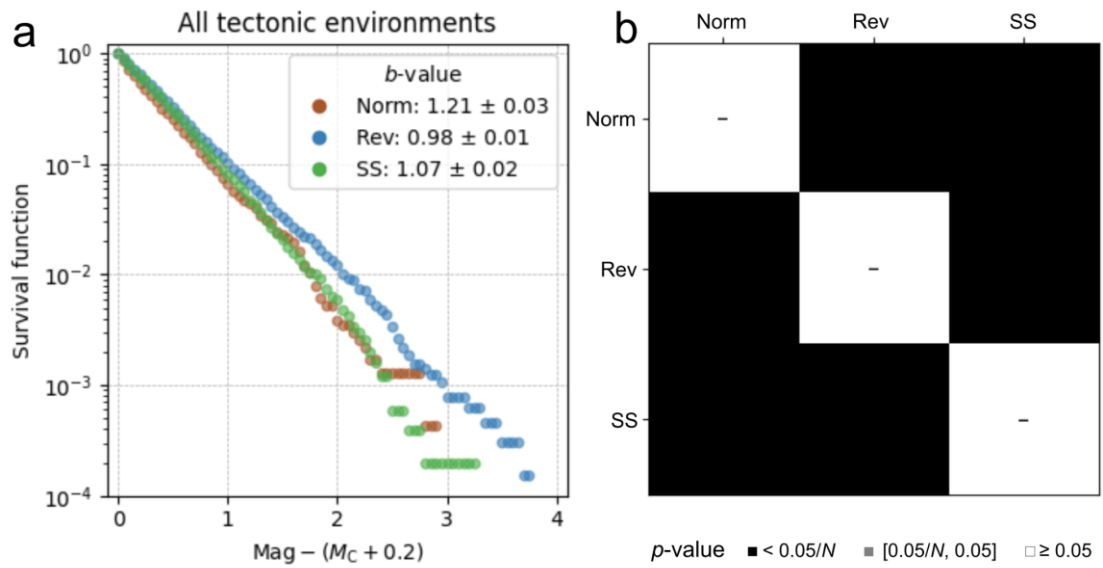


**Figure 12.2 MFDs and  $p$ -values of the Utsu test between  $b$ -values with the second solution of the CMT.**

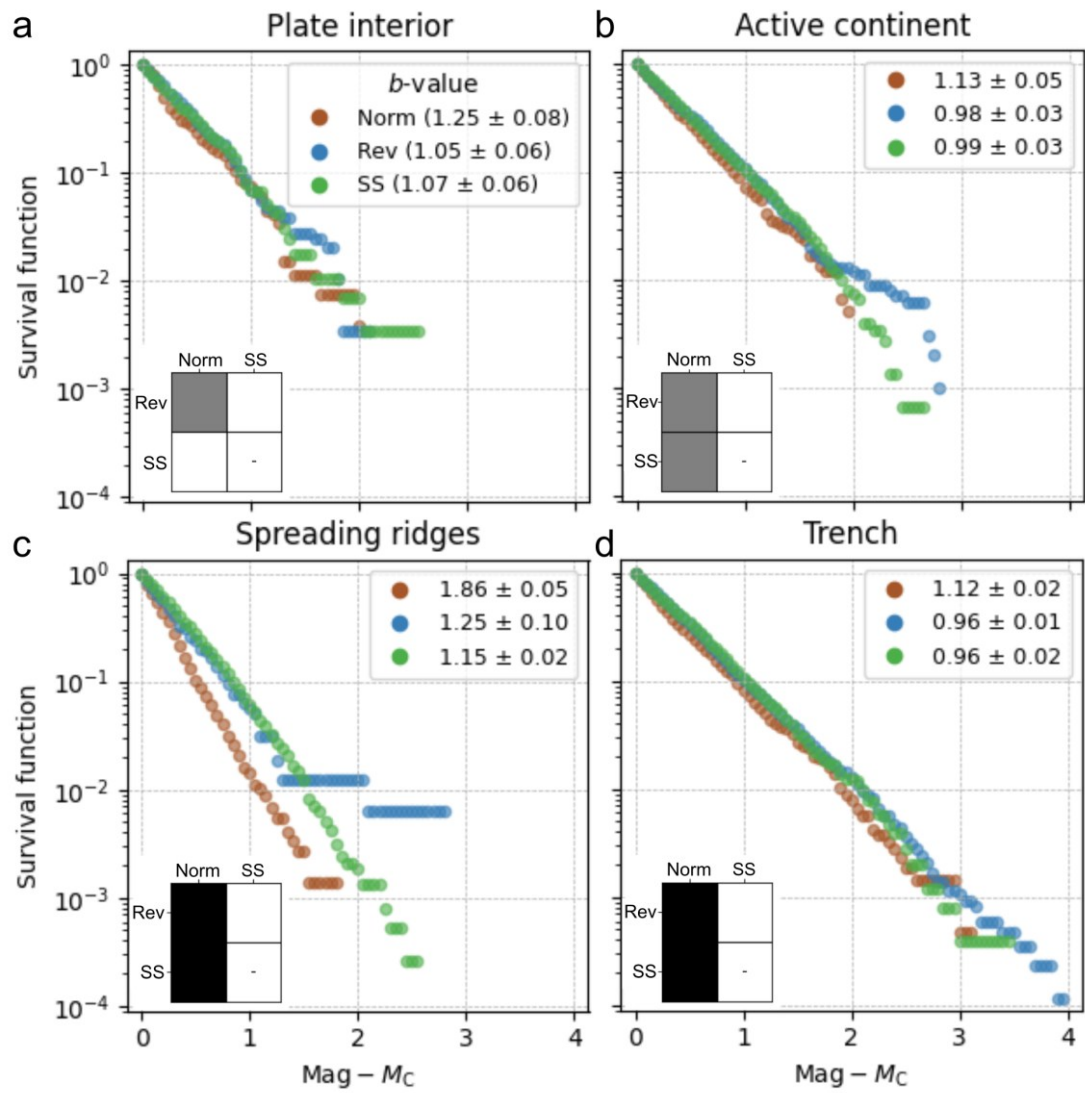


**Figure 12.3** MFDs and  $p$ -values of the Utsu test between  $b$ -values using a more conservative estimation of the  $M_C$ .

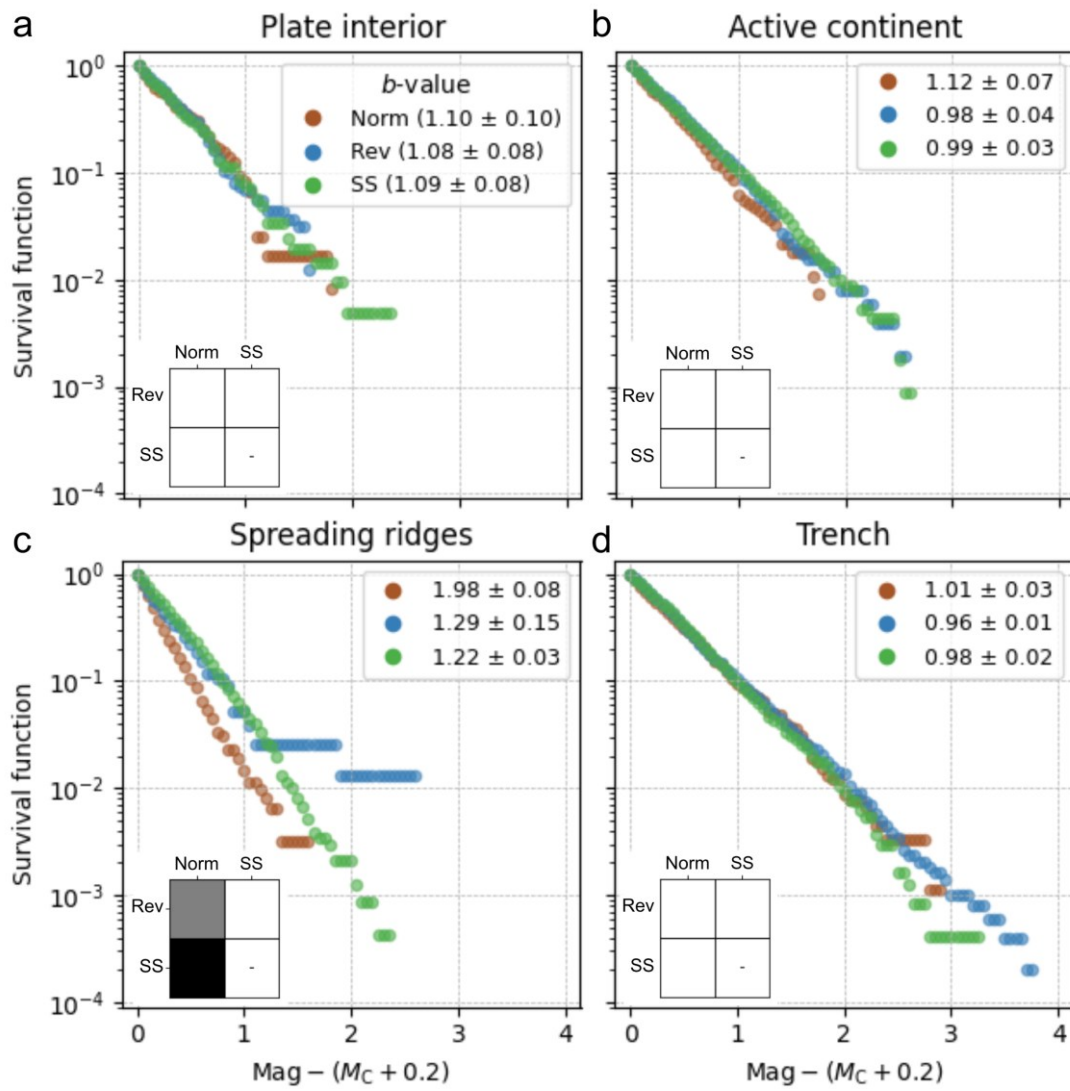
For confirmatory results using the second solution of the CMT see Figure 12.4.



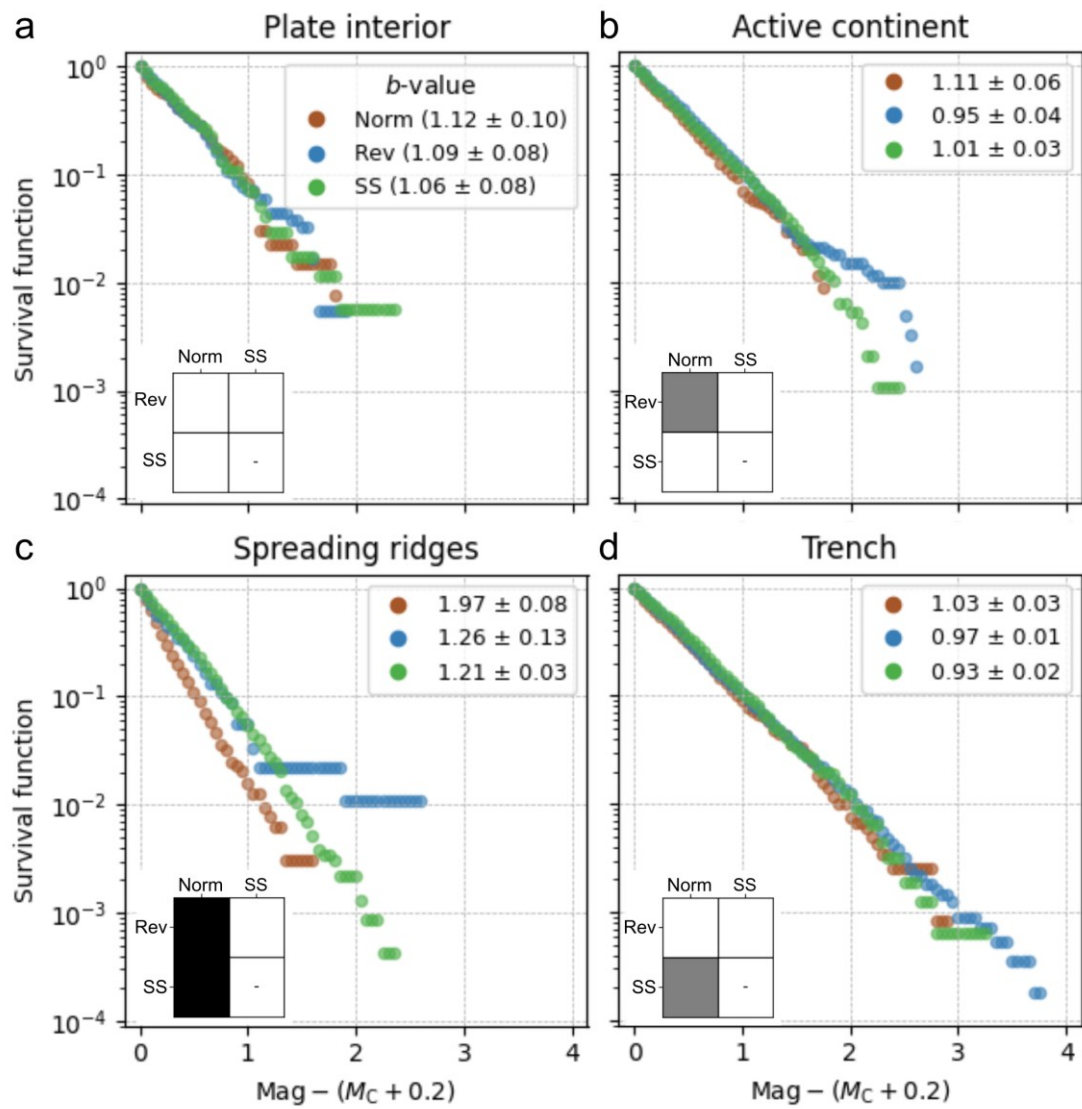
*Figure 12.4 MFDs and  $p$ -values of the Utsu test between  $b$ -values using the second solution of the CMT and a more conservative estimation of the  $M_C$ .*



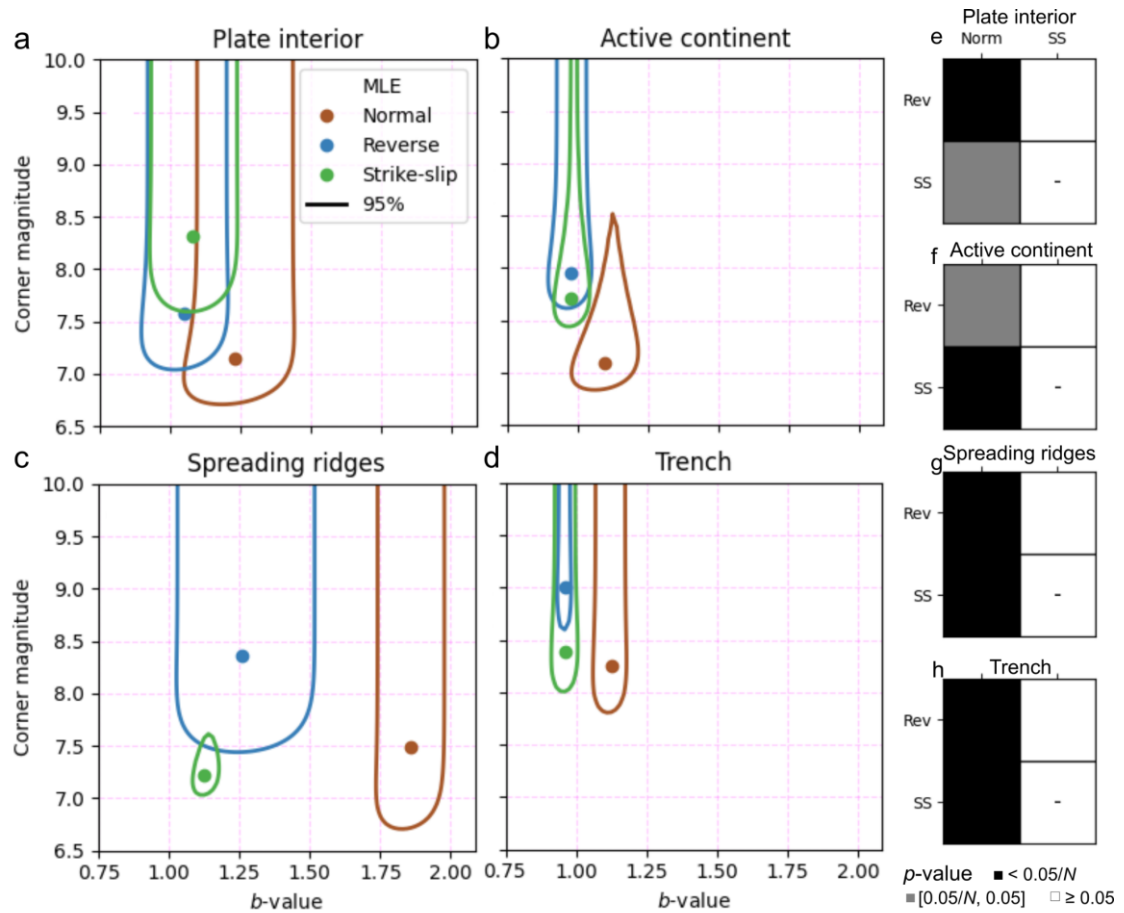
*Figure 12.5 MFDs for each type of kinematics in each tectonic environment using the second solution of the CMT.*



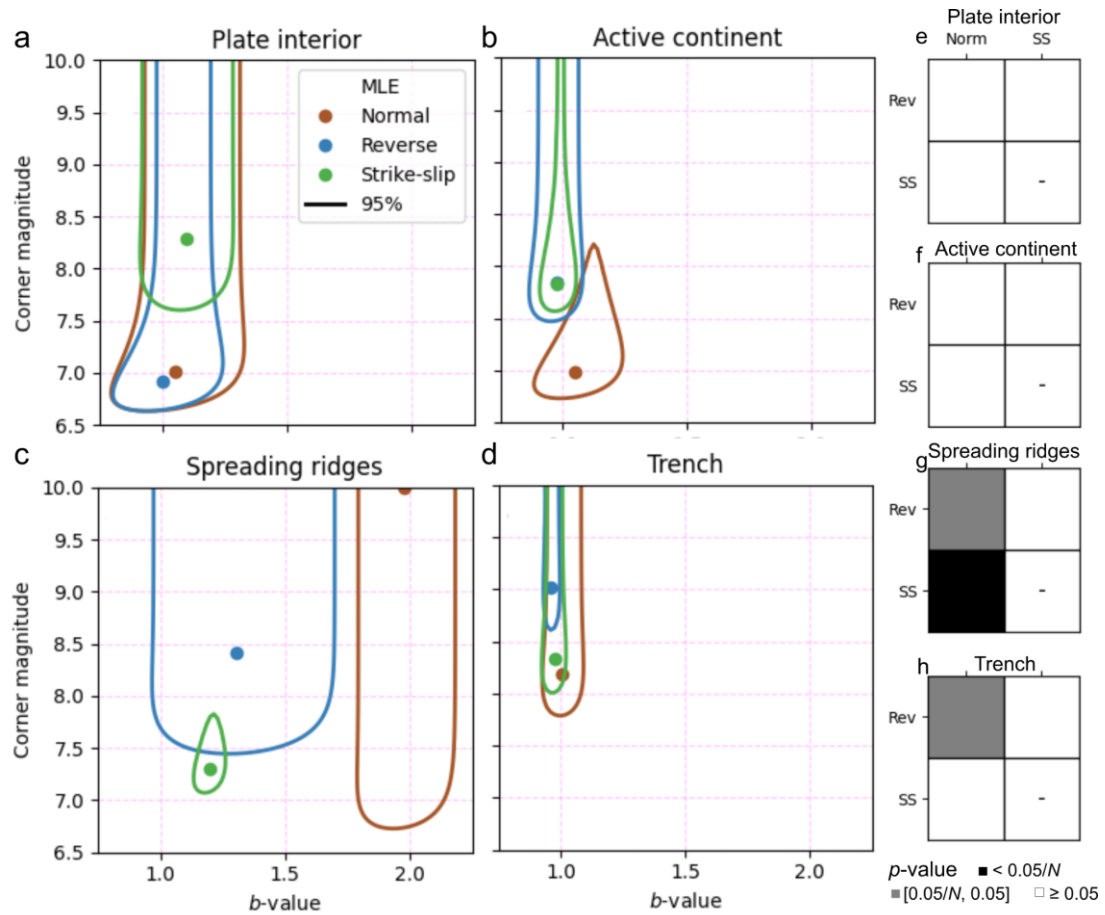
*Figure 12.6 MFDs for each type of kinematics in each tectonic environment using a more conservative estimation of the  $M_C$ .*



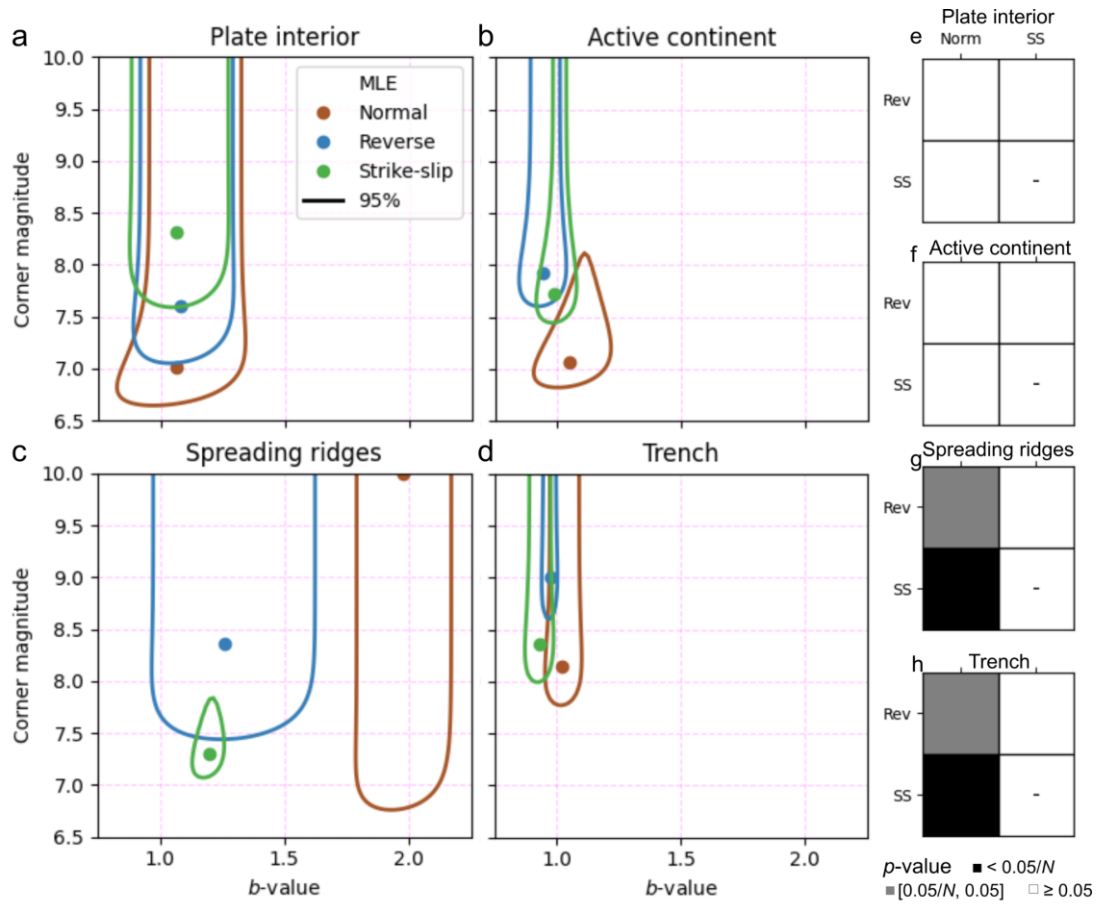
**Figure 12.7** MFDs for each type of kinematics in each tectonic environment using the second solution of the CMT and a more conservative estimation of the  $M_C$ .



**Figure 12.8** Maximum likelihood estimations and 95% confidence level of the parameters of the tapered GR in different tectonic environments with the second solution of the CMT.



**Figure 12.9** Maximum likelihood estimations and 95% confidence level of the parameters of the tapered GR in different tectonic environments with a more conservative estimation of the  $M_C$ .



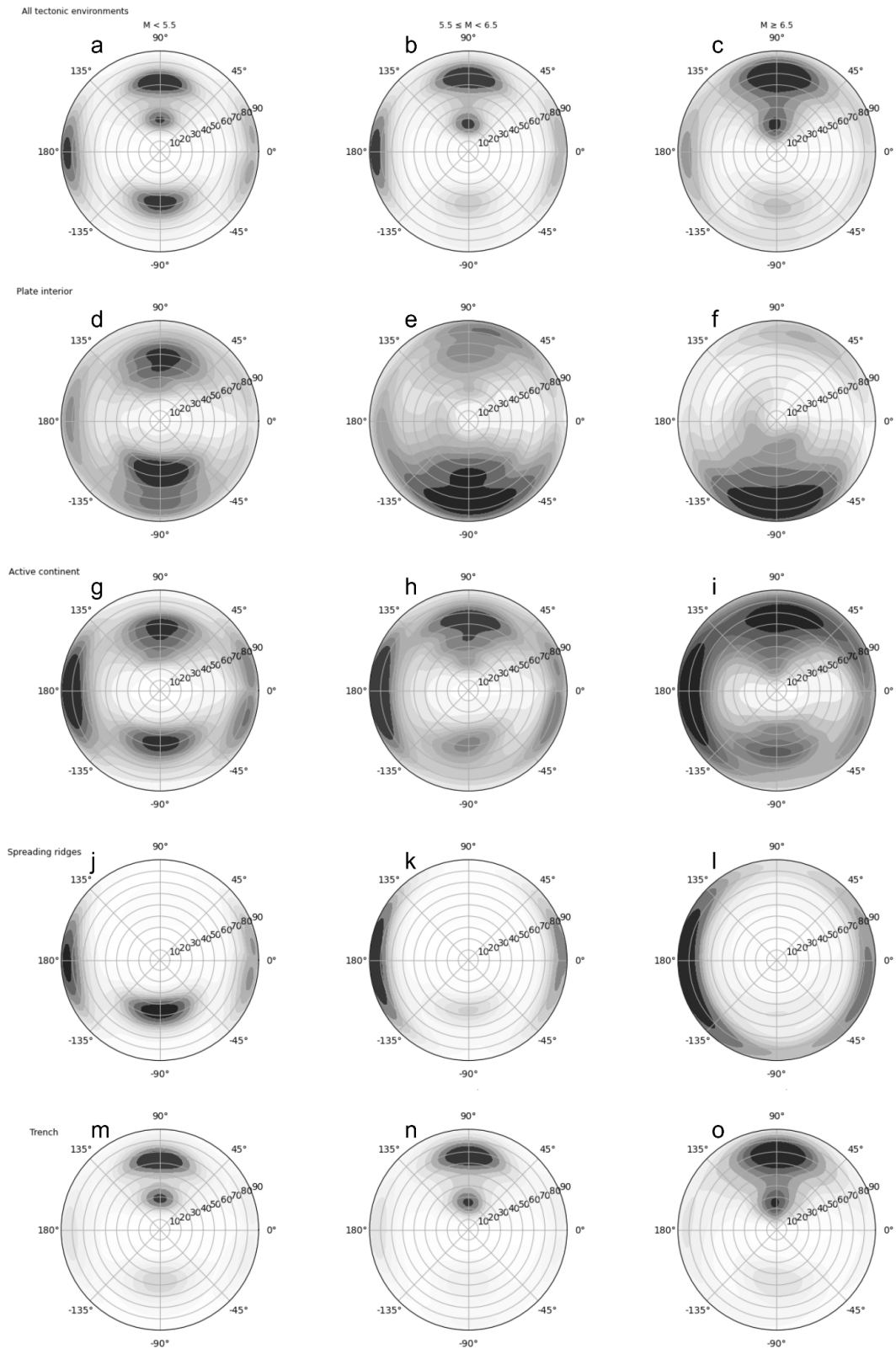
**Figure 12.10** Maximum likelihood estimations and 95% confidence level of the parameters of the tapered GR in different tectonic environments with the second solution of the CMT and a more conservative estimation of the  $M_C$ .



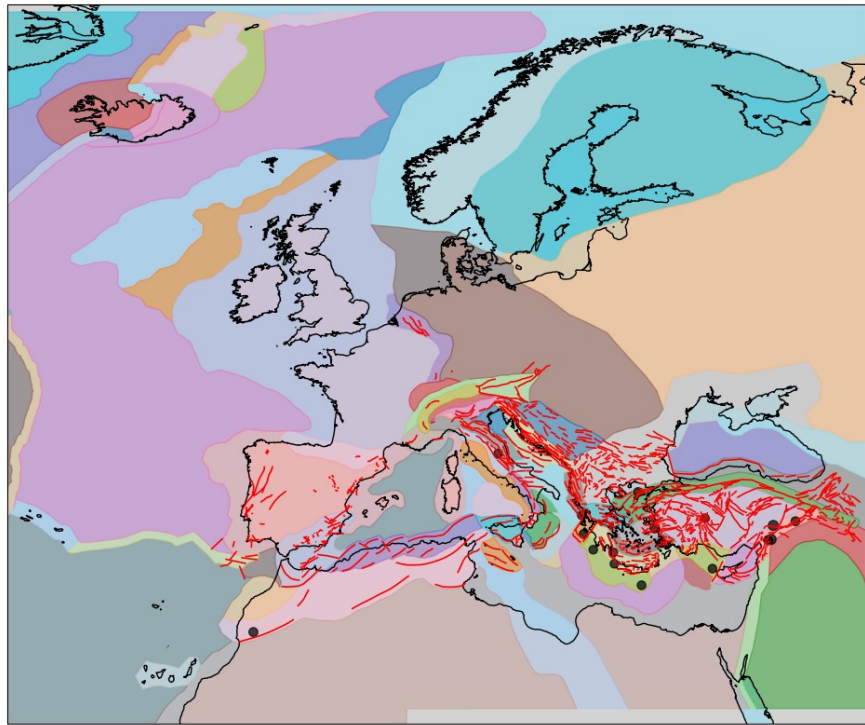
# 13

## SUPPORTING INFORMATION FOR CHAPTER

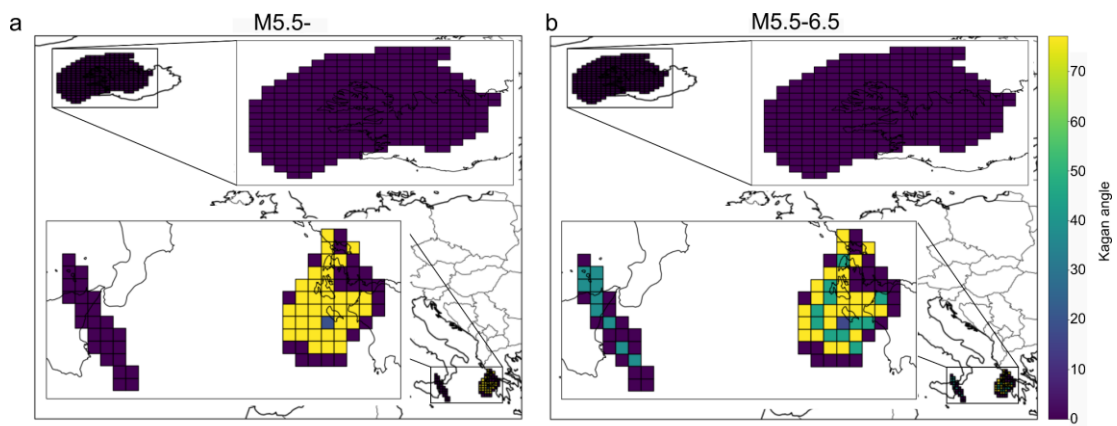
6



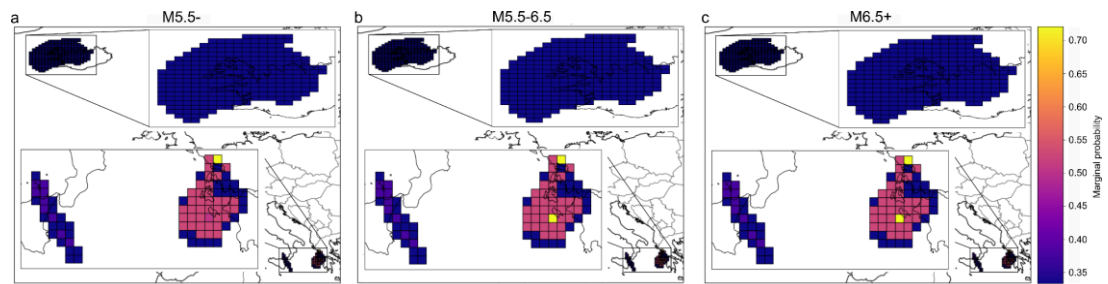
**Figure 13.1** Polar representation of rake and dip angles according to the magnitude range and to the tectonic environment.



*Figure 13.2 Map of the study regions with seismic events and faults considering only events with magnitude larger than 6.5.*



*Figure 13.3 Map of the Kagan angle considering only events with magnitude smaller than 5.5 and between 5.5 and 6.5.*



*Figure 13.4 Marginal probability maps for magnitudes smaller than 5.5, between 5.5 and 6.5 and larger than 6.5.*



## 14

## SUPPORTING INFORMATION FOR CHAPTER

## 7

## 14.1 Nearest-neighbor

We apply the NN declustering method (Zaliapin, *et al.* 2020), which quantifies the proximity between earthquakes in a combined space–time–magnitude domain. Each event is characterized by its occurrence time, hypocentral coordinates, and magnitude. Proximity is defined asymmetrically in time, with temporal and spatial distances normalized by the magnitude of the earlier event. This formulation allows each earthquake to be linked to a unique “nearest neighbor” (its parent), creating parent–offspring relationships that form seismic clusters.

In seismic catalogs, the logarithmic distribution of nearest-neighbor distances is typically bimodal: one mode corresponds to background seismicity, and the other to clustered events (aftershocks). Scaling distances by the parent magnitude adjusts the spatial “attraction domain” of larger earthquakes, improving the identification of aftershock sequences.

The algorithm requires three main parameters: (i) the fractal dimension  $d$  of hypocenters (typically estimated with the correlation integral), (ii) the initial cutoff proximity  $\eta_0$  (iii) the cluster threshold  $\eta$ .

In our application, the workflow proceeds by first filtering the catalog for completeness ( $M_{min}$  in Table 14.1) and time interval, and then computing nearest-neighbor distances for all events:

$$R_{ij} = r_{ij}^d \times 10^{bM_i/2} \quad (14.1)$$

$$T_{ij} = t_{ij} \times 10^{bM_i/2} \quad (14.2)$$

The proximity of an event  $j$  to the previous one  $i$  is defined as:

$$n_{ij} = \begin{cases} t_{ij}(r_{ij})^d 10^{-wm_i}, & t_{ij} > 0 \\ \infty, & t_{ij} \leq 0 \end{cases} \quad (14.3)$$

where  $w$  is the weight dependent on the magnitude.

The parameters used for the NN clustering are listed in Table 14.1.

The distribution of  $\log_{10}(\eta)$  is used to distinguish clustered and background events (Figure 7.1), with a bimodal histogram typically observed. Mainshocks are identified as the largest magnitude events in each cluster, and aftershocks are linked through the parent–child tree.

## 14.2 Catalog simulation

We generated synthetic earthquake catalogs using the simplETAS algorithm (Mancini and Marzocchi 2023), a simplified version of the classical ETAS model (see section “Probabilistic forecasting models: the ETAS model”). While

the full ETAS formulation involves the simultaneous estimation of numerous parameters from observed data—a task that is both computationally demanding and potentially unstable—*simpl*ETAS reduces this complexity by estimating only two parameters locally: the total background seismicity rate ( $\mu$ ) and the productivity parameter ( $K$ ). All other parameters are fixed to standard values obtained from empirical studies, under the assumption that such fixed values remain valid at a regional scale without compromising the realism of the simulated clustering.

The *simpl*ETAS model preserves key physical constraints of the full formulation, such as the equality between the  $\alpha$  and  $\beta$  parameters, ensuring that event scaling remains physically plausible and consistent with established empirical scaling laws in earthquake sequences. This simplification enables the efficient generation of synthetic catalogs that reproduce the statistical features of observed seismicity, without requiring prior declustering or independence assumptions within sequences. All the parameters used for the simulation are listed in Table [14.1](#).

In addition to time, location, and magnitude, the output of *simpl*ETAS includes a label identifying whether each event belongs to the background seismicity or is triggered, as well as explicit “parent–child” links that specify which event generated each event. In the synthetic catalogs used here, background events are shown as grey dots (Figure [7.2](#)), and parental links are represented as solid lines.

### 14.3 Mainshock and foreshock identification

After creating the catalog (see “[Catalog simulation](#)”) and removing background events, we identify mainshocks using the Gardner and Knopoff (1974, GK) declustering method. In this approach, earthquakes are classified as mainshocks if no larger events occur within magnitude-dependent spatial and temporal windows. The spatial window,  $R(M)$ , defines the radius within which aftershocks are considered associated with a mainshock of magnitude  $M$  and is given by:

$$R(M) = 10^{a_1 M + b_1} \quad (14.4)$$

The temporal window,  $T(M)$ , expressed in years, defines the time interval for clustering and follows two separate formulas depending on the mainshock magnitude:

$$T(M) = 10^{a_2 M + b_2} \quad (14.5)$$

These magnitude-dependent windows are based on empirical observations that larger earthquakes typically generate aftershocks over larger areas and for longer durations. Within this framework, an earthquake is classified as a mainshock only if no larger events are detected inside its corresponding space-time window.

We then classify the sequences according to the magnitude class to which the mainshock belongs:  $M4.0-4.5$ ,  $M4.5-5.0$ ,  $M5.0-5.5$ ,  $M5.5-6.0$ .

Once we have identified the mainshocks we identify the foreshocks through the links provided by the ETAS model.

Starting with the mainshock, we reconstruct the chain of events that has led to it finally arriving at the first background event that started the chain (ETAS type-1). Then we identify all the first-generation events that have a parent that is in that chain and that occurred before the mainshock (ETAS type-2).

After applying this procedure, we observe that some sequences partially overlap, sharing common events linked to multiple mainshocks. These overlapping sequences are excluded from further analyses to avoid double counting and ensure that each foreshock sequence is uniquely associated with a single mainshock.

**Table 14.1 Parameters used for the catalog simulation and for the NN declustering.**

The star (\*) indicates the parameters that have been estimated, the others are fixed.

| ETAS simulation parameters |                     |           |                       |                        |                           |
|----------------------------|---------------------|-----------|-----------------------|------------------------|---------------------------|
| $b$ -value                 | $M_{min}$           | $M_{max}$ | $\mu^*$ (events/year) | $K^*$                  | $\alpha = \beta$          |
| 1.0                        | 1.5                 | 7.5       | 18.2713               | 0.0473                 | $b$ -value log (10)       |
| $p$                        | $C$ (days)          | $\gamma$  | $q$                   | $D$ (km <sup>2</sup> ) | Simulation length (years) |
| 1.15                       | 0.005               | 1.5       | 1.5                   | 1                      | 50                        |
| NN parameters              |                     |           |                       |                        |                           |
| $d$                        | $\log_{10}(\eta_0)$ |           |                       |                        |                           |
| 1.6                        | -5                  |           |                       |                        |                           |



## Bibliography

Agnew, D. C., and L. M. Jones. "Prediction probabilities from foreshocks." *Journal of Geophysical Research: Solid Earth* 96, no. B7 (1991): 11959-11971.

Aki, K. "A probabilistic synthesis of precursory phenomena." *Earthquake prediction: an international review* 4 (1981).

Aki, K. "Maximum likelihood estimate of  $b$  in the formula  $\log(N)=a-bM$  and its confidence limits." *Bull. Earthq. Res. Inst. Tokyo Univ.* 43 (1965): 237-239.

Aki, K., and P. G. Richards. *Quantitative Seismology*. University Science Books, 2002.

Amitrano, D. "Brittle-ductile transition and associated seismicity: Experimental and numerical studies and relationship with the  $b$  value." *Journal of Geophysical Research: Solid Earth* 108, no. B1 (2003).

Anderson, E. M. "The dynamics of faulting." *Trans. Edinburgh Geol. Soc.* 8, no. 3 (1905): 387-402.

Ankerst, M., M. M. Breunig, H. P. Kriegel, and J. Sander. "OPTICS: Ordering points to identify the clustering structure." *ACM Sigmod Record* 28, no. 2 (1999): 49-60.

- Baiesi, M., and M. Paczuski. "Scale-free networks of earthquakes and aftershocks." *Phys. Rev. E* 69, no. 6 (2004).
- Bakun, W. H., and W. B. Joyner. "The ML scale in central California." *Bulletin of the Seismological Society of America* 74, no. 5 (1984): 1827-1843.
- Barchi, M. R., and et al. "The influence of subsurface geology on the distribution of earthquakes during the 2016-2017 Central Italy seismic sequence." *Tectonophysics* 807 (2021): 228797.
- Basili, R., and et al. "The Database of Individual Seismogenic Sources (DISS), version 3: Summarizing 20 years of research of Italy's earthquake geology." *Tectonophysics* 453, no. 1-4 (2008): 20-43.
- . *The European Database of Seismogenic Faults (EDSF)*. 2013. <https://seismofaults.eu/edsf13> (accessed August 2025).
- Basili, R., and et al. "The making of the NEAM Tsunami Hazard Model 2018 (NEAMTHM18)." *Frontiers in Earth Science* 8 (2021).
- Bayliss, K., M. Naylor, and I. G. Main. "Developing a background seismicity model for operational earthquake forecasting in Italy." *Geophysical Journal International* 242, no. 3 (2025).
- Bayliss, K., M. Naylor, and I. G. Main. "Probabilistic identification of earthquake clusters using rescaled nearest neighbour distance networks." *Geophysical Journal International* 217, no. 1 (2019): 487-503.

- Bedford, J. D., T. Hirose, and Y. Hamada. "Rapid fault healing after seismic slip." *Journal of Geophysical Research: Solid Earth* 128, no. 6 (2023).
- Bethmann, F., N. Deichmann, and P. M. Mai. "Scaling relations of local magnitude versus moment magnitude for sequences of similar earthquakes in Switzerland." *Bulletin of the Seismological Society of America* 101, no. 2 (2011): 515-534.
- Bird, P. "An updated digital model of plate boundaries." *Geochemistry, Geophysics, Geosystems* 4, no. 3 (2003): 1027.
- Bird, P., and Y. Y. Kagan. "Plate-tectonic analysis of shallow seismicity: Apparent boundary width, beta, corner magnitude, coupled lithosphere thickness, and coupling in seven tectonic settings." *Bulletin of the Seismological Society of America* 94, no. 6 (2004): 2380-2399.
- Bolton, D. C., S. Shreedharan, J. Riviere, and C. Marone. "Acoustic energy release during the laboratory seismic cycle: Insights on laboratory earthquake precursors and prediction." *Journal of Geophysical Research: Solid Earth* 125, no. 8 (2020).
- Bolton, D. C., S. Shreedharan, J. Riviere, and C. Marone. "Frequency-magnitude statistics of laboratory foreshocks vary with shear velocity, fault slip rate, and shear stress." *Journal of Geophysical Research: Solid Earth* 126, no. 11 (2021).

Bonferroni, C. "Teoria statistica delle classi e calcolo delle probabilità."

*Pubblicazioni del R istituto superiore di scienze economiche e commerciali di Firenze*. 8 (1936): 3-62.

Bonini, L., and et al. "Testing different tectonic models for the source of the Mw

6.5, 30 October 2016, Norcia earthquake (central Italy): A youthful normal fault, or negative inversion of an old thrust?" *Tectonics* 38, no. 3 (2019): 990-1017.

Cheng, C., C. Hui, J. Yang, and S. Shen. "The relationship between heat flow

and seismicity in global tectonically active zones." *Open Geosciences* 12, no. 1 (2020): 1430-1439.

Chiaraluce, L., and et al. "The 2016 central Italy seismic sequence: A first look

at the mainshocks, aftershocks, and source models." *Seismological Research Letters* 88, no. 3 (2017): 757-771.

Collettini, C., and E. Tinti. "The influence of lithology and fault source volume

on the magnitude-frequency-distribution of earthquakes." *Geophys. Res.* 52, no. 2 (2025).

Collettini, C., M. R. Barchi, N. De Paola, F. Trippetta, and E. Tinti. "Rock and

fault rheology explain differences between on fault and distributed seismicity." *Nature Communications* 13, no. 1 (2022): 5627.

Convertito, V., R. De Matteis, and N. A. Pino. "Evidence for static and dynamic

triggering of seismicity following the 24 August 2016, MW = 6.0,

- Amatrice (Central Italy) earthquake." *Pure and Applied Geophysics* 174, no. 10 (2017): 3663-3672.
- Corrado, P., M. Herrmann, and W. Marzocchi. "Earthquake magnitude correlations expose short-term catalog incompleteness." *Seismological Research Letters* 96, no. 2A (2025): 909-919.
- Corral, A. "Dependence of earthquake recurrence times and independence of magnitudes on seismicity history." *Tectonophysics* 424, no. 3-4 (2006): 177-193.
- Das, S., and C. H. Scholz. "Theory of time-dependent rupture in the Earth." *Journal of Geophysical Research: Solid Earth* 86, no. B7 (1981): 6039-6051.
- Davidson, J., and A. Green. "Are earthquake magnitudes clustered?" *Physical Review Letters* 106, no. 10 (2011).
- Davies, J. H. "Global map of solid Earth surface heat flow." *Geochemistry, Geophysics, Geosystems* 14, no. 10 (2013): 4608-4622.
- De Arcangelis, L., C. Godano, E. Lippiello, and M. Nicodemi. "Statistical physics approach to earthquake occurrence and forecasting." *Physics Reports* 628 (2016): 1-91.
- Deichmann, N. "Theoretical basis for the observed break in the ML/MW scaling between small and large earthquakes." *Bulletin of the Seismological Society of America* 107, no. 2 (2017): 505-520.

- Dziewonski, A. M., T. -A. Chou, and J. H. Woodhouse. "Determination of earthquake source parameters from waveform data for studies of global and regional seismicity." *Journal of Geophysical Research* 86 (1981): 2825-2852.
- Ekström, G., M. Nettles, and A. M. Dziewonski. "The global CMT project 2004-2010: Centroid-moment tensors for 13,017 earthquakes." *Phys. Earth Planet. Inter.*, 2012: 1-9.
- Ellsworth, W. L., and G. C. Beroza. "Seismic evidence for an earthquake nucleation phase." *Science* 268, no. 5212 (1995): 851-855.
- Elst, N. J. van der. "b-positive: A robust estimator of aftershock magnitude distribution in transiently incomplete catalogs." *Journal of Geophysical Research: Solid Earth* 126, no. 2 (2021).
- Enescu, B., S. Hainzl, and Y. Ben-Zion. "Correlations of seismicity patterns in Southern California with surface heat flow data." *Bulletin of the Seismological Society of America* 99, no. 6 (2009): 3114-3123.
- Ester, M., H. P. Kriegel, J. Sander, and X. Xu. "A density-based algorithm for discovering clusters in large spatial databases with noise." *International conference on knowledge discovery and data mining (KDD96)*. 1996. 226-231.

- Fagereng, A., and A. Beall. "Is complex fault zone behaviour a reflection of rheological heterogeneity?" *Philosophical transaction of Royal Society A* 379, no. 2193 (2021).
- Farrell, J., S. Husen, and R. B. Smith. "Earthquake swarm and b-value characterization of the Yellowstone volcano-tectonic system." *Journal of Volcanology and Geothermal Research* 188, no. 1-3 (2009): 260-276.
- Felzer, K. R., and E. E. Brodsky. "Decay of aftershock density with distance indicates triggering by dynamic stress." *Nature* 441 (2006): 735-738.
- Felzer, K. R., R. E. Abercrombie, and G. Ekstrom. "A common origin for aftershocks, foreshocks, and multiplets." *Bulletin of the Seismological Society of America* 94, no. 1 (2004): 88-98.
- Felzer, K. R., T. W. Becker, R. E. Abercrombie, G. Ekstrom, and J. R. Rice. "Triggering of the 1999 Mw 7.1 Hector Mine earthquake by aftershocks of the 1992 Mw 7.3 Landers earthquake." *Journal of Geophysical Research* 107, no. B9 (2002).
- Frohlich, C., and S. D. Davis. "Single-link cluster analysis as a method to evaluate spatial and temporal properties of earthquake catalogues." *Geophysical Journal International* 100, no. 1 (1990): 19-32.
- García-Hernández, R., L. D'Auria, J. Barrancos, G. D. Padilla, and N. M. Pérez. "Multiscale Temporal and Spatial Estimation of the b-value." *Seismological Research Letters* 92, no. 6 (2021): 3712-3724.

- Gardner, J. K., and L. Knopoff. "Is the sequence of earthquakes in southern California, with aftershocks removed, Poissonian?" *Bulletin of the Seismological Society of America* 64, no. 5 (1974): 1363-1367.
- Geist, E. L., and T. Parsons. "Probabilistic analysis of tsunami hazards." *Natural Hazards* 37 (2006): 277-314.
- Gibbons, J. D., and S. Chakraborti. *Nonparametric Statistical Inference*. CRC Press, 2003.
- Godano, C., A. Tramelli, G. Petrillo, E. Bellucci Sessa, and E. Lippiello. "The dependence on the moho depth of the b-value of the Gutenberg-Richter law." *Bulletin of the Seismological Society of America* 112, no. 4 (2022): 1921-1934.
- Goebel, T. H. W., D. Schorlemmer, T. W. Becker, G. Dresen, and C. G. Sammis. "Acoustic emissions document stress changes over many seismic cycles in stick-slip experiments." *Geophysical Research Letters* 40 (2013): 2049-2054.
- González, Á. "Improvements and heterogeneities of the Global Centroid Moment Tensor catalog." *Seismological Research Letters* 40, no. 10 (2024): 2049-2054.
- Grünthal, G., R. Wahlstrom, and D. Stromeyer. "The unified catalogue of earthquakes in central, northern, and northwestern Europe (CENEC)-

Updated and expanded to the last millennium." *Journal of Seismology* 13, no. 4 (2009): 517-541.

Gulia, L., A. P. Rinaldi, T. Tormann, G. Vannucci, B. Enescu, and S. Wiemer. "The effect of a mainshock on the size distribution of the aftershocks." *Geophysical Research Letters* 45, no. 24 (2018): 13-277.

Gulia, L., and S. Wiemer. "Real-time discrimination of earthquake foreshocks and aftershocks." *Nature* 574, no. 7777 (2019): 193-199.

Gulia, L., and S. Wiemer. "The influence of tectonic regimes on the earthquake size distribution: A case study for Italy." *Geophysical Research Letters* 37, no. 10 (2010).

Gulia, L., S. Wiemer, and G. Vannucci. "Pseudoprospective evaluation of the foreshocks traffic-light system in Ridgecrest and implications for the aftershock hazard assessment." *Seismological Society of America* 91, no. 5 (2020): 2828-2842.

Gulia, L., T. Tormann, S. Wiemer, M. Herrmann, and S. Seif. "Short-term probabilistic earthquake risk assessment considering time-dependent  $b$  values." *Geophysical Research Letters* 43, no. 3 (2016): 1100-1108.

Gutenberg, B., and C. Richter. "Frequency of earthquakes in California." *Bulletin of the Seismological Society of America* 34 (1944): 185-188.

Hainzl, S. "Rate-dependent incompleteness of earthquake catalogs." *Seismological Research Letters* 87, no. 2A (2016): 337-344.

Hanks, T. C., and D. M. Boore. "Moment-magnitude relations in theory and practice." *Journal of Geophysical Research: Solid Earth* 89, no. B7 (1984): 6229-6235.

Hardebeck, J. L., K. R. Felzer, and A. J. Michael. "Improved tests reveal that the accelerating moment release hypothesis is statistically insignificant." *Journal of Geophysical Research* 113, no. B8 (2008): 529.

Hauksson, E., W. Yang, and P. M. Shearer. "Waveform relocated earthquake catalog for southern California (1981 to June 2011)." *Bulletin of the Seismological Society of America* 102, no. 5 (2012): 2239-2244.

Helmstetter, A. "Comparison of short-term and time-independent earthquake forecast models for southern California." *Bulletin of the Seismological Society of America* 96, no. 1 (2006): 90-106.

Helmstetter, A., and D. Sornette. "Foreshocks explained by cascades of triggered seismicity." *Journal of Geophysical Research: Solid Earth* 108, no. B10 (2003).

Herrmann, M., and W. Marzocchi. "Inconsistencies and lurking pitfalls in the magnitude-frequency distribution of high-resolution earthquake catalogs." *Seismological Research Letters* 92, no. 2A (2021): 909-922.

Herrmann, M., and W. Marzocchi. *Mc-Lilliefors: a completeness magnitude that complies with the exponential-like GutenbergRichter relation*. 2020.

- Herrmann, M., E. Piegari, and W. Marzocchi. "Revealing the spatiotemporal complexity of the magnitude distribution and b-value during an earthquake sequence." *Nature Communications* 13, no. 1 (2022): 5087.
- Hirata, T. "A correlation between the b-value and the fractal dimension of earthquakes." *Journal of Geophysical Research: Solid Earth* 94, no. B6 (1989): 7507-7514.
- Huc, M., and I. G. Main. "Anomalous stress diffusion in earthquake triggering: Correlation length, time dependence, and directionality." *Journal of Geophysical Research: Solid Earth* 108, no. B7 (2003).
- Iwata, T. "Low detection capability of global earthquakes after the occurrence of large earthquakes: Investigation of the Harvard CMT catalogue." *Geophysical Journal International* 174, no. 3 (2008): 849-856.
- Jones, W. M., B. Wang, S. Xu, and T. J. Fitch. "The foreshock sequence of the February 5, 1975, Haicheng earthquake (M=7.3)." *Journal of Geophysical Research: Solid Earth* 87, no. B6 (1982): 4575-4584.
- Jordan, T. H. "Operational earthquake forecasting state of knowledge and guidelines for utilization." *Annals of Geophysics* 54 (2011): 315-391.
- Kagan, Y. Y. "3-D rotation of double-couple earthquake sources." *Geophysical Journal International* 106, no. 3 (1991): 709-716.
- Kagan, Y. Y. "Accuracy of modern global earthquake catalogs." *Phys. Earth Planet. Inter.* 135, no. 2-3 (2003): 173-209.

Kagan, Y. Y. "Is earthquake seismology a hard, quantitative science? ." *Seismicity Patterns, their Statistical Significance and Physical Meaning*. , 1999: 233-258.

Kagan, Y. Y. "Is earthquake seismology a hard, quantitative science?" *Pure and applied geophysics* 155, no. 2 (1999): 233-258.

Kagan, Y. Y. "Seismic moment distribution revisited: I. Statistical results." *Geophysical Journal International* 148, no. 3 (2002): 520-541.

Kagan, Y. Y. "Short-term properties of earthquake catalogs and models of earthquake source." *Bulletin of the Seismological Society of America* 94, no. 4 (2004): 1207-1228.

Kagan, Y. Y., and D. D. Jackson. "Statistical earthquake focal mechanism forecasts." *Geophysical Journal International* 197, no. 1 (2014): 620-629.

Kagan, Y. Y., P. Bird, and D. D. Jackson. "Earthquake patterns in diverse tectonic zones of the globe." *Pure and Applied Geophysics*. 167 (2010): 721-741.

Kanamori, H. "The nature of seismicity patterns before large earthquakes." *Earthquake prediction: An international review* 4 (1981): 1-19.

Kostrov, B. V. "Seismic moment and energy of earthquakes, and seismic flow of rock." *Izv. Acad. Sci. USSR, Phys. Solid Earth* 1 (1974): 23-44.

- Kubo, H., M. Naoi, and M. Kano. "Recent advances in earthquake seismology using machine learning." *Earth Planets and Space* 76, no. 1 (2024): 36.
- Kwiatek, G., and et al. "Months-long seismicity transients preceding the 2023 Mw 7.8 Kahramanmaras earthquake, Turkiye." *Nature Communications* 14, no. 1 (2023): 7534.
- Laske, G., G. Masters, Z. Ma, and M. Pasyanos. "Update on CRUST1. 0-A 1-degree global model of Earth's crust." *Geophysical research abstracts* 15, no. 15 (2013): 2658.
- Laurenti, L., G. Paoletti, E. Tinti, F. Galasso, C. Collettini, and C. Marone. "Probing the evolution of fault properties during the seismic cycle with deep learning." *Nature Communications* 15, no. 1 (2024): 10025.
- Lee, E. J., D. Mu, W. Wang, and P. Chen. "Weighted Template-Matching Algorithm (WTMA) for improved foreshock detection of the 2019 Ridgecrest earthquake sequence." *Bulletin of the Seismological Society of America* 110, no. 4 (2020): 1832-1844.
- Lee, E. J., W. Y. Liao, D. Mu, W. Wang, and P. Chen. "GPU-accelerated automatic microseismic monitornig algorithm (Gamma) and its application to the 2019 Ridgecrest earthquake sequence." *Seismological Research Letters* 91, no. 4 (2020): 2062-2074.

- Leeman, J. R., D. M. Saffer, M. M. Scuderi, and C. Marone. "Laboratory observations of slow earthquakes and the spectrum of tectonic fault slip models." *Nature Communications* 7, no. 1 (2016): 11104.
- Lippiello, E., and G. Petrillo. "b-more-incomplete and b-more-positive: Insights on a robust estimator of magnitude distribution." *Journal of Geophysical Research: Solid Earth* 129 (2024).
- Lippiello, E., C. Godano, and L. De Arcangelis. "The earthquake magnitude is influenced by previous seismicity." *Geophysical Research Letters* 39, no. 5 (2012).
- Lippiello, E., F. Giacco, W. Marzocchi, C. Godano, and L. De Arcangelis. "Statistical features of foreshocks in instrumental and ETAS catalogs." *Pure and Applied Geophysics* 174 (2017): 1679-1697.
- Lippiello, E., G. Petrillo, C. Godano, and L. Dal Zilio. "Toward recognizing the waveform of foreshocks." *Geophysical Research Letters* 52 (2025).
- Lippiello, E., L. De Arcangelis, and C. Godano. "Influence of time and space correlations on earthquake magnitude." *Physical Review Letters* 100, no. 3 (2008).
- Liu, M., M. Zhang, W. Zhu, W. L. Ellsworth, and H. Li. "Rapid characterization of the July 2019 Ridgecrest, California, earthquake sequence from raw seismic data using machine learning phase picker." *Geophysical Research Letters* 47, no. 4 (2020).

- Lyakhovsky, V., Y. Ben-Zion, and A. Agnon. "Distributed damage, faulting, and friction." *Journal of Geophysical Research* 102, no. B12 (1997): 27635-27649.
- Maćkiewicz, A., and W. Ratajczak. "Principal components analysis (PCA)." *Computers & Geosciences* 19, no. 3 (1993): 303-342.
- Main, I. G. "A characteristic earthquake model of the seismicity preceding the eruption of Mount St. Helens." *Phys. Earth Planet. Int.*, 1987: 283-293.
- Main, I., P. G. Meredith, and C. Jones. "A reinterpretation of the precursory seismic b-value anomaly from fracture mechanics." *Geophysical Journal International* 96, no. 1 (1989): 131-138.
- Mancini, S., and W. Marzocchi. "SimpleTAS: A benchmark earthquake forecasting model suitable for operational purposes and seismic hazard analysis." *Seismological Research Letters* 95, no. 1 (2024): 38-49.
- Manganiello, E., M. Herrmann, and W. Marzocchi. "New physical implications from revisiting foreshock activity in southern California." *Geophysical Research Letters* 50, no. 1 (2023).
- Marzocchi, W., and L. Sandri. "A review and new insights on the estimation of the b-value and its uncertainty." *Annals of Geophysics* 46, no. 6 (2003): 1271-1282.

Marzocchi, W., I. Spassiani, A. Stallone, and M. Taroni. "How to be fooled searching for significant variations of the b-value." *Geophysical Journal International* 220, no. 3 (2020): 1845-1856.

Marzocchi, W., L. Sandri, A. Heuret, and F. Funiciello. "Where giant earthquakes may come." *Journal of Geophysical Research: Solid Earth* 121 (2016): 7322-7336.

Mignan, A. "The debate on the prognostic value of earthquake foreshocks: A meta-analysis." *Scientific Reports* 4, no. 1 (2014): 4099.

Mirwald, A., L. Mizrahi, and S. Wiemer. "How to b-significant when analyzing b-value variations." *Seismological Research Letters* 95, no. 6 (2024): 3343-3359.

Montuori, C., M. Murru, and G. Falcone. "Spatial variation of the b-value observed for the periods preceding and following the 24 August 2016, Amatrice earthquake (ML 6.0) (Central Italy)." *Annals of Geophysics* 59 (2016).

Munafò, I., L. Malagnini, and L. Chiaraluce. "On the relationship between Mw and ML for small earthquakes." *Bulletin of the Seismological Society of America* 106, no. 5 (2016): 5402-2408.

Muzellec, T., G. De Landro, G. Camanni, G. M. Adinolfi, and A. Zollo. "The complex 4D multi-segmented rupture of the 2014 Mw 6.2 Northern

- Nagano Earthquake revealed by high-precision aftershock locations." *Tectonophysics* 898 (2025): 230641.
- Nandan, S., G. Ouillon, and D. Sornette. "Are large earthquakes preferentially triggered by other large events?" *Journal of Geophysical Research: Solid Earth* 127, no. 8 (2022).
- Nandan, S., G. Ouillon, S. Wiemer, and D. Sornette. "Objective Estimation of Spatially Variable Parameters of Epidemic Type Aftershock Sequence Model: Application to California." *Journal of Geophysical Research: Solid Earth* 122 (2017): 5118-5143.
- Nanjo, K. Z. "Were changes in stress state responsible for the 2019 Ridgecrest, California, earthquakes?" *Nature Communications* 11, no. 1 (2020): 3082.
- Nanjo, K. Z., and A. Yoshida. "Anomalous decrease in relatively large shocks and increase in the p and b values preceding the April 16, 2016, M7.3 earthquake in Kumamoto, Japan." *Earth Planets and Space* 69, no. 1 (2017): 13.
- Nanjo, K. Z., N. Hirata, K. Obara, and K. Kasahara. "Decade-scale decrease in b value prior to the M 9-class 2012 Tohoku and 2004 Sumatra quakes." *Geophysical Research Letters* 39, no. 20 (2012).

- Nanjo, K., and et al. "Predictability study on the aftershock sequence following the 2011 Tohoku-Oki, Japan, earthquake. First results." *Geophysical Journal International* 191, no. 2 (2012): 653-658.
- Ogata, Y. "Statistical models for earthquake occurrences and residual analysis for point processes." *Journal of the American Statistical Association* 83, no. 401 (1988): 9-27.
- Ogata, Y., and K. Katsura. "Analysis of temporal and spatial heterogeneity of magnitude frequency distribution inferred from earthquake catalogues." *Geophysical Journal International* 113, no. 3 (1993): 727-738.
- Pacheco, J. F., and L. R. Skyes. "Seismic moment catalog of large shallow earthquakes, 1900 ro 1989." *Bulletin of the Seismological Society of America* 82, no. 3 (1992): 1306-1349.
- Page, M. T., and N. J. van Der Elst. "Aftershocks preferentially occur in previously active areas." *The Seismic Record* 2, no. 2 (2022): 100-106.
- Pearson, K. "On lines and planes of closest fit to systems of points in space." *The London, Edinburgh and Dublin Philosophical Magazine and Journal of Science*. 2, no. 11 (1901): 559-572.
- Petrillo, G., and J. Zhuang. "The debate on the earthquake magnitude correlations: A meta analysis." *Scientific Reports* 12, no. 1 (2022): 20683.

Petrillo, G., and J. Zhuang. "Verifying the magnitude dependence in earthquake occurrence." *Physical Review Letters* 131, no. 15 (2023): 14101.

Petrucelli, A., et al. "The influence of faulting style on the size-distribution of global earthquakes." *Earth and Planetary Science Letters* 527 (2019): 115791.

Petrucelli, A., G. Vannucci, B. Lolli, and P. Gasperini. "Harmonic fluctuation of the slope of the frequency-magnitude distribution (b-value) as a function of the angle of rake,," *Bulletin of the Seismological Society of America* 108, no. 4 (2018): 1864-1876.

Piegari, E., G. Camanni, M. Mercurio, and W. Marzocchi. "Illuminating the hierarchical segmentation of faults through an unsupervised learning approach applied to seismic sequences." *Earth and Space Science*. 11, no. 10 (2024).

Piegari, E., M. Herrmann, and W. Marzocchi. "3-D spatial cluster analysis of seismic sequences through density-based algorithms." *Geophysical Journal International* 230, no. 3 (2022): 2073-2088.

Pondrelli, S. *European-Mediterranean Regional Centroid-Moment Tensors Catalog (RCMT)*. 2002.

Quinn, D. P., and B. L. Ehlmann. "A PCA-based framework for determining remotely sensed geological surface orientations and their statistical quality." *Earth and Space Science* 6 (2019): 1378-1408.

Reasenber, P. A., and L. M. Jones. "Earthquake hazard after a mainshock in California." *Science* 243, no. 4895 (1989): 1173-1176.

Rice, J., and M. Cocco. "Seismic fault rheology and earthquake dynamics." *Tectonic faults: Agents of change on a dynamic Earth (Chapter 5)* 99-137 (2007): 99-138.

Rodríguez-Pérez, Q., M. Monterrubio-Velasco, F. R. Zuniga, C. M. Valdés-Gonzalez, and R. Arambula-Mendoza. "Spatial and temporal b-value characterization at Popocatepetl volcano, Central Mexico." *Journal of Volcanology and Geothermal Research* 417 (2021).

Roselli, P., W. Marzocchi, M. T. Mariucci, and P. Montone. "Earthquake focal mechanism forecasting in Italy for PSHA purposes." *Geophysical Journal International* 212, no. 1 (2018): 491-508.

Ross, Z. E., and et al. "Hierarchical interlocked orthogonal faulting in the 2019 Ridgecrest earthquake sequence." *Science* 366, no. 6463 (2019): 346-351.

Ross, Z. E., E. S. Cochran, D. T. Trugman, and J. D. Smith. "3D fault architecture controls the dynamism of earthquake swarms." *Science* 368, no. 6497 (2020): 1357-1361.

Scholz, C. H. "On the stress dependence of the earthquake b value." *Geophysical Research Letters* 42, no. 5 (2015): 1399-1402.

- Scholz, C. H. "The frequency-magnitude relation of microfracturing in rock and its relation to earthquakes." *Bulletin of the seismological society of America* 58, no. 1 (1968): 399-415.
- Schorlemmer, D., S. Wiemer, and M. Wyss. "Variations in earthquake-size distribution across different stress regimes." *Nature* 437, no. 7058 (2005): 539-542.
- Selva, J., and et al. "Quantification of source uncertainties in seismic probabilistic tsunami hazard analysis (SPTHA)." *Geophysical Journal International* 205, no. 3 (2016): 1780-1803.
- Selva, J., and W. Marzocchi. "Focal parameters, depth estimation, and plane selection of the worldwide shallow seismicity with  $M_s \geq 7.0$  for the period 1900-1976." *Geochemistry, Geophysics, Geosystems* 5, no. 5 (2004).
- Shelly, D. R. "A high-resolution seismic catalog for the initial 2019 Ridgecrest earthquake sequence: Foreshocks, aftershocks, and fault complexity." *Seismological Research Letters* 91, no. 4 (2020): 1971-1978.
- Spassiani, I., and G. Sebastiani. "Exploring the relationship between the magnitudes of seismic events." *Journal of Geophysical Research: Solid Earth* 121, no. 2 (2016): 903-316.
- Stallone, A., and W. Marzocchi. "Empirical evaluation of the magnitude-independence assumption." *Geophysical Journal International* 216, no. 2 (2019): 820-839.

- Sugan, M., S. Campanella, L. Chiaraluce, M. Michele, and A. Vuan. "The unlocking process leading to the 2016 Central Italy seismic sequence." *Geophysical Research Letters* 50, no. 5 (2023).
- Tan, Y. J., and et al. "Machine-learning-based high-resolution earthquake catalog reveals how complex fault structures were activated during the 2016-2017 central Italy sequence." *The Seismic Record* 1, no. 1 (2021): 11-19.
- Taroni, M. "Back to the future: Old methods for new estimation and test of the Gutenberg-Richter b-value for catalogues with variable completeness." *Geophysics Journal International* 224, no. 1 (2021): 337-339.
- Taroni, M. "Estimating the magnitude of completeness of earthquake catalogs using a simple random variable transformation." *The Seismic Record* 3, no. 3 (2023): 194-199.
- Taroni, M., and et al. "Prospective CSEP evaluation of 1-day, 3-month, and 5-yr earthquake forecasts for Italy." *Seismological Research Letters* 89, no. 4 (2018): 1251-1261.
- Taroni, M., and J. Selva. "A testable worldwide earthquake faulting mechanism model." *Seismological Research Letters* 92, no. 6 (2021): 3577-3585.
- Taroni, M., and M. M. C. Carafa. "Earthquake size distributions are slightly different in compression vs extension." *Communications Earth & Environment* 4, no. 1 (2023): 398.

- Taroni, M., J. Selva, and J. Zhuang. "Estimation of the tapered Gutenberg-Richter distribution parameters for catalogs with variable completeness: An application to the Atlantic ridge seismicity." *Applied Sciences* 11, no. 24 (2021): 12166.
- Tinti, S., and F. Mulargia. "Confidence intervals of b values for grouped magnitudes." *Bulletin of the Seismological Society of America* 77, no. 6 (1987): 2125-2134.
- Tormann, T., B. Enescu, J. Woessner, and S. Wiemer. "Randomness of megathrust earthquakes implied by rapid stress recovery after the Japan earthquake." *Nature Geoscience* 8, no. 2 (2015): 152-158.
- Tormann, T., S. Wiemer, and A. Mignan. "Systematic survey of high-resolution b value imaging along Californian faults: Influence on asperities." *Journal of Geophysical Research* 119, no. 3 (2014): 1-26.
- Utsu, T. "A statistical significance test of the difference in b-value between two earthquake groups." *J. Phys. Earth* 14, no. 2 (1966): 37-40.
- Utsu, T. "Magnitudes of earthquakes and occurrence of their aftershocks." *Zisin* 10, no. 2 (1957): 35-45.
- Valensise, G., and et al. "Fossil landscapes and youthful seismogenic sources in the central Apennines: Excerpts from the 24 August 2016, Amatrice earthquake and seismic hazard implications." *Annals of Geophysics* 59 (2016).

- Varini, E., A. Peresan, and J. Zhuang. "Topological comparison between the stochastic and the nearest-neighbor earthquake declustering methods through network analysis." *Journal of Geophysical Research: Solid Earth* 125, no. 8 (2020).
- Vere-Jones, D. "Forecasting earthquakes and earthquake risk." *International Journal of Forecasting* 11 (1995): 503-538.
- Vičić, B., A. Aoudia, A. Borghi, S. Momeni, and A. Vuan. "Seismicity rate changes and geodetic transients in Central Apennines." *Geophysical Research Letters* 47, no. 22 (2020).
- Villani, F., and et al. "A database of the coseismic effects following the 30 October 2016 Norcia earthquake in Central Italy." *Scientific Data* 5, no. 1 (2018): 1-11.
- Vuan, A., M. Sukan, L. Chiaraluce, and R. Di Stefano. "Loading rate variations along a mid-crustal shear zone preceding the Mw 6.0 earthquake of 24 August 2016 in Central Italy." *Geophysical Research Letters* 44 (2017): 12170-12180.
- Waldhauser, F., and W. L. Ellsworth. "A double-difference earthquake location algorithm: Method and application to the Northern Hayward fault, California." *Bulletin of the Seismological Society of America*. 90, no. 6 (2000): 1353-1368.

Waldhauser, F., M. Michele, L. Chiaraluce, R. Di Stefano, and D. P. Schaff.

"Fault planes, fault zone structure and detachment fragmentation resolved with high precision aftershock locations of the 2016-2017 Central Italy sequence." *Geophysical Research Letters* 48, no. 16 (2021).

Waldhauser, F., W. L. Ellsworth, D. P. Schaff, and A. Cole. "Streaks, multiplets,

and holes: High-resolution spatio-temporal behavior of Parkfield seismicity." *Geophysical Research Letters* 31, no. 18 (2004).

Walters, R. J., and et al. "Dual control of fault intersections on stop-start rupture

in the 2016 Central Italy seismic sequence." *Earth and Planetary Science Letters* 500, no. 5 (2018): 1-14.

Warren, N. W., and G. V. Latham. "An experimental study of thermally induced

microfracturing and its relation to volcanic seismicity." *Journal of Geophysical Research* 75, no. 23 (1970): 4455-4464.

Wetzler, N., T. Lay, and E. E. Brodsky. "Global characteristics of observable

foreshocks for large earthquakes." *Seismological Research Letters* 94, no. 5 (2023): 2312-2325.

Wiemer, S., and M. Wyss. "Mapping spatial variability of the frequency-

magnitude distribution of earthquakes." *Advances in Geophysics* 45 (2002): 259-302.

- Wiemer, S., and M. Wyss. "Mapping the frequency-magnitude distribution in asperities: An improved technique to calculate recurrence times?" *Journal of Geophysical Research* 102, no. B7 (1997): 15115-15128.
- Wiemer, S., and M. Wyss. "Minimum magnitude of completeness in earthquake catalogs: Examples from Alaska, the Western United States, and Japan." *Bulletin of the Seismological Society of America* 90 (2000): 859-869.
- Woessner, J., and S. Wiemer. "Assessing the quality of earthquake catalogues: Estimating the magnitude of completeness and its uncertainty." *Bulletin of the Seismological Society of America* 95, no. 2 (2005): 684-698.
- Wyss, M., K. Shimazaki, and S. Wiemer. "Mapping active magma chambers by b values beneath the off-Ito volcano, Japan." *Journal of Geophysical Research: Solid Earth* 102, no. B9 (1997): 20413-20422.
- Xiong, Q., M. R. Brudzinski, D. Gossett, Q. Lin, and J. C. Hampton. "Seismic magnitude clustering is prevalent in field and laboratory catalogs." *Nature communications* 14, no. 1 (2023): 2056.
- Zaccagnino, D., F. Vallianatos, G. Michas, L. Telesca, and C. Doglioni. "Are foreshocks fore-shocks?" *Journal of Geophysical Research: Solid Earth* 129 (2024).
- Zaliapin, I., A. Gabrielov, V. Keilis-Borok, and H. Wong. "Clustering analysis of seismicity and aftershock identification." *Physical Review Letters* 101, no. 1 (2008).

Zaliapin, I., and Y. Ben-Zion. "Earthquake clusters in southern California I: Identification and stability." *Journal of Geophysical Research: Solid Earth* 118 (2013).

Zhong, S., C. Xu, L. Yi, and Y. Li. "Focal mechanisms of the 2016 central Italy earthquake sequence inferred from high-rate GPS and broadband seismic waveforms." *Remote Sensing*. 10, no. 4 (2018): 512.

Zhuang, J., and S. Touati. "Stochastic simulation of earthquake catalogs." *Community Online Resource for Statistical Seismicity Analysis*, 2015.