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OPTIMIZING SEISMIC B-VALUES IN THE JAVA REGION THROUGH VORONOI-BASED OK1993 MODELLING

OPTIMALISASI NILAI-B SEISMIK DI WILAYAH JAWA MELALUI PEMODELAN OK1993 BERBASIS VORONOI

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Abstract. The spatial variation of b-values in seismically active regions provides critical insight into the stress state and rupture potential of fault systems. This study focuses on the Java region and surrounding subduction zones, where detailed mapping of b-values remains uncertain despite high seismic risk. A Voronoi-based ensemble modelling framework is implemented, incorporating the Ogata-Katsura 1993 (OK1993) formulation and spatial sampling via Sobol sequences to ensure uniform partitioning. Earthquake data from 1995 onward were compiled and harmonized into moment magnitude (Mw) using conversion equations from the Indonesian Earthquake Source and Hazard Map 2017. The OK1993 model enables estimation of b-values optimized via trust-constr and initialized with maximum likelihood estimates. The results reveal that high b-values ($b > 1.2$) dominate offshore southwest Lampung and south of Bali, whereas low b-values ($b < 0.8$) appear parts of the Sumatra fault near the Sunda Strait, faults across Java, and thrusts north of Bali and Lombok. Moderate b-values (0.8–1.0) extend along the southern Java trench and may represent partially coupled megathrust segments. Interestingly, the low b-value zones may indicate locked asperities and potential seismic gap segments, especially along southern Java, where large ruptures have not occurred in recent decades. This study demonstrates the utility of spatially adaptive, data-driven approaches in capturing complex tectonic segmentation and supports their integration into future seismic hazard assessments in Indonesia, particularly in Java and its surrounding regions.

Abstrak. *Variasi spasial nilai-b di wilayah yang aktif secara seismik memberikan wawasan penting tentang kondisi tegangan dan potensi pecahnya sistem sesar. Studi ini berfokus pada wilayah Jawa dan zona subduksi di sekitarnya, di mana pemetaan detail nilai-b masih belum pasti meskipun risiko seismiknya tinggi. Kerangka kerja pemodelan ensemble berbasis Voronoi diimplementasikan, menggabungkan formulasi Ogata-*

Katsura 1993 (OK1993) dan pengambilan sampel spasial melalui sekuens Sobol untuk memastikan partisi yang seragam. Data gempa bumi sejak tahun 1995 dan seterusnya dikompilasi dan diharmonisasikan menjadi magnitudo momen (Mw) menggunakan persamaan konversi dari Peta Sumber dan Bahaya Gempa Bumi Indonesia 2017. Model OK1993 memungkinkan estimasi nilai-b yang dioptimalkan melalui trust-constr dan diinisialisasi dengan estimasi kemungkinan maksimum. Hasilnya mengungkapkan bahwa nilai-b yang tinggi (b > 1,2) mendominasi lepas pantai barat daya Lampung dan selatan Bali, sementara nilai-b yang rendah (b < 0,8) muncul di bagian patahan Sumatra dekat Selat Sunda, patahan di Jawa, dan dorongan di utara Bali dan Lombok. Nilai-b sedang (0,8–1,0) memanjang di sepanjang palung selatan Jawa dan dapat mewakili segmen megathrust yang terhubung sebagian. Menariknya, zona nilai-b yang rendah dapat menunjukkan asperitas yang terkunci dan segmen celah seismik potensial, terutama di sepanjang Jawa selatan, di mana pecah besar belum terjadi dalam beberapa dekade terakhir. Studi ini menunjukkan kegunaan pendekatan yang adaptif secara spasial dan berbasis data dalam menangkap segmentasi tektonik yang kompleks dan mendukung integrasinya ke dalam penilaian bahaya seismik di masa depan di Indonesia, khususnya di Jawa dan wilayah sekitarnya.

1. INTRODUCTION

Indonesia is located in one of the most tectonically active regions on Earth, situated at the convergent boundary where the Indo Australian Plate subducts beneath the Eurasian Plate along the Sunda megathrust. This geodynamic setting produces frequent seismic activity across Java and its surrounding regions, including the Sunda Trench (Simons et al., 2007; McCaffrey, 2009). Understanding the spatial and temporal distribution of earthquakes is crucial for seismic hazard assessment, particularly in densely populated and economically vital regions such as Java. One of the key parameters used to characterize seismicity is the b-value of the Gutenberg–Richter frequency–magnitude distribution. This parameter reflects the relative proportion of small to large earthquakes and is widely interpreted as an indicator of stress conditions, tectonic segmentation, and material heterogeneity in the Earth's crust (Scholz, 2015; Wiemer & Wyss, 2002; Schorlemmer et al., 2005).

Despite its wide application, accurate estimation of b-values remains challenging due to methodological limitations. Traditional approaches often rely on subjective choices of fixed search radii or minimum event counts, leading to inconsistencies and potential bias in the resulting b-value maps. These limitations are particularly problematic in regions with heterogeneous seismic networks or non uniform data density. Consequently, classical b-value estimates may either underestimate or overemphasize spatial variations, thereby affecting the reliability of seismic hazard models (Wiemer & Wyss, 2002; Tormann et al., 2014; Kamer & Hiemer, 2015).

To address these issues, recent studies have adopted data-driven approaches that reduce subjectivity and improve robustness. One such approach is based on spatial partitioning using Voronoi tessellation, which allows for adaptive, non-uniform subdivision of the study area based on randomly distributed nodes (Jiang et al., 2021). Within each Voronoi cell, b-values are estimated using the OK1993 model, a probabilistic formulation introduced by Ogata and Katsura (1993) that accounts for magnitude detection completeness and enables maximum likelihood estimation of the Gutenberg–Richter parameters. The model complexity is evaluated using the Bayesian Information Criterion (BIC), and an ensemble of the best-performing models is selected to produce a median b-value and its associated uncertainty, expressed through the Median Absolute Deviation (MAD). This ensemble-based Voronoi–OK1993 approach has been successfully applied in studies of spatial heterogeneity in seismicity (e.g. Jiang et al., 2021), demonstrating improved resolution and reduction of sampling bias compared to traditional methods.

This study applies the Voronoi-based OK1993 optimization method to analyze the spatial distribution of b-values in Java and adjacent areas. Earthquake catalogs were compiled and harmonized to Moment Magnitude (Mw) before analysis. The results provide a comprehensive view of seismic frequency–magnitude behaviour in the region, revealing zones of relatively high and low b-values that may be linked to tectonic segmentation, fault locking, or variations in stress regime. The findings are expected to contribute to a more objective and data-informed foundation for regional seismic hazard assessments in Indonesia.

2. LITERATURE REVIEW

The Gutenberg–Richter (G–R) law has long been used to describe the statistical relationship between the frequency and magnitude of earthquakes. The b-value in this relation quantifies the relative occurrence of small versus large earthquakes and is widely interpreted as a proxy for crustal stress conditions, fault maturity, and heterogeneity in seismogenic zones (Scholz, 2015; Wiemer & Wyss, 2002). Numerous studies have shown that regions with low b-values may be associated with high stress accumulation or locked fault patches, whereas high b-values may reflect increased material heterogeneity or distributed fault damage, particularly in high-damage zones near fluid injection, whereas elevated pore pressure generally leads to lower b-values due to accelerated fault activation and smoother stress fields (Thapa et al., 2025; Schorlemmer & Wiemer, 2005).

However, the reliability of spatial b-value mapping is often limited by subjective methodological choices. Traditional methods generally involve dividing the study region into regular grids and estimating b-values within circular windows of fixed radius or fixed event count (Wiemer & Wyss, 2002). While widely used, these approaches have been criticized for their parameter sensitivity and data redundancy due to overlapping sampling volumes (Kamer & Hiemer, 2013). Such methods may exaggerate spatial fluctuations in b-values, especially when data density varies significantly across the region (Kagan, 1999).

To overcome these limitations, more recent studies have adopted data-driven and nonparametric approaches for estimating b-values. One of the most prominent is the Voronoi-based method introduced by Kamer and Hiemer (2015), which avoids fixed grids and instead partitions space into Voronoi cells based on randomly placed nodes. Within each cell, b-values are estimated using maximum likelihood techniques, and model complexity is evaluated using information-theoretic criteria such as the Bayesian Information Criterion (BIC). This approach has been demonstrated to produce more stable and statistically robust b-value maps, as it reduces the risk of overfitting and compensates for uneven data coverage.

Complementing this, Jiang et al. (2021) incorporated the Ogata-Katsura 1993 (OK1993) model to better account for magnitude completeness when estimating b-values. The OK1993 model introduces a magnitude detection function that allows simultaneous estimation of the completeness threshold (Mc) and the b-value, even in regions with limited or unevenly distributed seismic data. When combined with Voronoi-based spatial partitioning and ensemble averaging over multiple realizations, this method improves the resolution and reliability of b-value estimation.

These advances underscore a shift toward more objective and reproducible techniques in seismological studies, particularly in high-risk regions such as Indonesia. By building on these foundations, the present study aims to apply a Voronoi-based OK1993 optimization framework for the first time to earthquake data in Java and surrounding regions. This literature basis not only supports the methodological choices but also highlights the relevance of such approaches for seismic hazard assessment in complex tectonic environments.

3. RESEARCH METHODS

This study employs a data-driven framework to estimate the spatial distribution of Gutenberg–Richter *b*-values across Java and surrounding areas. The methodology integrates Voronoi tessellation for adaptive spatial partitioning and the Ogata–Katsura 1993 (OK1993) model for estimation of the optimized *b*-value. A key improvement introduced in this study is the use of Sobol sequence sampling to generate spatial node distributions for Voronoi tessellation, replacing the conventional pseudorandom approach. This results in a more uniform coverage of spatial nodes, reducing clustering and under-sampling in certain areas.

3.1. Earthquake Catalog Preparation

We compiled an earthquake catalog covering the Java region and adjacent subduction zones, limited to events from 1995 onward to ensure temporal completeness. The initial dataset consisted of 62,043 earthquake records, which were then processed through magnitude unification and filtering. All magnitudes were converted to moment magnitude (Mw) using empirical conversion equations. These conversions were based on the empirical relationships provided in Irsyam et al. (2020), documented in the *Indonesian Earthquake Source and Hazard Map 2017* published by the Pusat Studi Gempa Nasional (PuSGeN), Ministry of Public Works and Housing, which serves as the national standard for seismic hazard research in Indonesia.

The conversion process was restricted to four common magnitude types: MW (moment magnitude), MS (surface-wave magnitude), ML (local magnitude), and MB (body-wave magnitude). These are the most widely used magnitude scales in regional and global earthquake catalogs, each representing different physical aspects of seismic energy measurement. Since empirical relationships for converting other magnitude types to Mw were not available, events with unsupported or undefined types were excluded. After this filtering, the catalog was reduced to 57,072 events with valid Mw values. Further restriction to events occurring from 1995 onward, based on completeness analysis, resulted in a final working dataset of 50,460 earthquakes.

The dataset was cleaned to remove duplicated events and constrained to entries with complete time, location, and magnitude information. Preliminary analyses, including magnitude–time plots and frequency–magnitude distributions, were conducted to assess magnitude consistency, detect completeness thresholds, and define the appropriate time window for statistical modelling.

3.2. Uniform Spatial Partitioning Using Sobol Sequence

Traditional Voronoi-based studies use pseudorandom distributions of seed points to partition the study area into cells. In this study, we improve the spatial uniformity of tessellation by generating node coordinates using a *Sobol low-discrepancy sequence*, a quasi-random technique known for better space-filling properties (Sobol', 1967). Unlike standard random sampling, the Sobol sequence generates points that are more evenly distributed over the spatial domain, helping to avoid over-clustering of Voronoi seeds in certain areas and undersampling in others. This ensures that each realization of the Voronoi model explores a more uniform partitioning of the spatial domain.

Each Voronoi tessellation is created by placing a number of nodes (ranging from 2 to 40) according to the Sobol distribution. For each number of nodes, 100 independent realizations are performed, resulting in a total of 3900 of spatial models.

3.3. OK1993 Model Formulation

For each Voronoi cell in a given tessellation, the *b*-value and completeness function are estimated using the OK1993 model (Ogata & Katsura, 1993). This model introduces a detection probability function $q(M|\mu, \sigma)$, defined as:

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

The probability density of observed magnitudes is:

$$P(M|\beta, \mu, \sigma) = \frac{\beta e^{-\beta(M-\mu)+\frac{\beta^2\sigma^2}{2}} q(M|\mu, \sigma)}{\int_{-\infty}^{\infty} \beta e^{-\beta(M-\mu)+\frac{\beta^2\sigma^2}{2}} q(M|\mu, \sigma) dM} \quad (2)$$

The log-likelihood function for a series of magnitudes M_i in a given cell is:

$$\ln L(\theta) = n \ln \beta - \sum_{i=1}^{n} [\beta M_i - \ln q(M_i|\mu, \sigma)] + n\beta\mu - \frac{n\beta^2\sigma^2}{2} \quad (3)$$

Here, $\beta = b \cdot \ln(10)$, and the parameter vector $\theta = (\beta, \mu, \sigma)$ is estimated using maximum likelihood optimization. The optimization process was implemented using the trust-constr algorithm from the scipy.optimize.minimize module in Python, a trust-region method well-suited for constrained nonlinear optimization problems (Conn et al., 2000; Virtanen et al., 2020).

Initial parameter values for the OK1993 model were estimated using the standard maximum likelihood estimator (MLE) by Aki (1965) for *b*-value:

$$b_{MLE} = \frac{\log_{10}(e)}{\overline{M} - M_{min}} \quad (4)$$

where $\overline{M}$ is the mean magnitude and M_{min} is the minimum magnitude in each Voronoi cell. The initial values of μ and σ were computed directly from the mean and standard deviation of magnitudes in each cell. All computations were conducted in Python with parallel processing using the multiprocessing library. Data for each model and tessellation realization were stored in HDF5 format, which ensures integrity and performance during parallel read/write operations.

3.4. Model Selection and Ensemble Analysis

Each spatial model is evaluated based on its overall model quality using the Bayesian Information Criterion (BIC):

$$BIC = -\ln L(\theta) + \frac{k}{2} \ln n \quad (5)$$

where k is the number of free parameters and n is the number of events. From the entire pool of tessellation models, the top 100 models with the lowest BIC values are selected. The ensemble median and median absolute deviation (MAD) of the *b*-values across these best-performing models are computed at each spatial location to quantify both central tendency and uncertainty.

In this study, the number of data points n in the BIC formulation was divided by 10. This empirical adjustment was applied to reduce the BIC's tendency to over-penalize complex models with more Voronoi cells, which would otherwise consistently favor low-resolution models with fewer cells. However, this adjustment is problem-specific and may not be necessary in other case studies where event density and model resolution are balanced.

3.5. Output Maps and Interpretation

The final products include spatial maps of median *b*-values, MAD, and the number of valid *b*-values contributing to each cell. These maps provide insights into the seismic regime of the region, highlighting zones with anomalously low *b*-values, which may indicate locked asperities or high-stress accumulation along subduction and crustal fault systems in and around Java.

Events with magnitudes greater than Mw 6.0 are represented by black circles, with sizes proportional to their magnitudes. The black lines with triangular teeth indicate thrust faults and the trench interface (commonly referred to as the subduction interface or megathrust boundary), while plain black lines represent normal and strike-slip faults (Irsyam et al., 2020).

4. RESULTS AND DISCUSSION

4.1. Seismicity Patterns, Magnitude Consistency, and Adaptive b-value Modeling

The earthquake catalog reveals distinct spatial patterns of seismicity across Java and its surrounding tectonic domains. As shown in **Figure 1**, seismic events are densely clustered along the Java Trench, reaffirming the subduction interface as the principal seismic source, while inland and back-arc activity signals the presence of crustal fault systems. The occurrence of several large-magnitude events near the trench suggests localized zones of strain accumulation that may correspond to locked segments or asperities. Complementing this, **Figure 2** summarizes the catalog's magnitude types and source distribution, highlighting the heterogeneity in recording practices and the predominance of local magnitude (ML), which necessitates magnitude unification for consistent seismicity modelling.

To ensure comparability across events, all magnitudes were converted to moment magnitude (Mw), and completeness was evaluated. **Figure 3a** demonstrates a stable lower-magnitude threshold beginning in 1995, justifying the temporal cutoff used for analysis. **Figure 3b** shows that most Mw values were derived from ML, followed by MS and MB, consistent with regional reporting standards. **Figure 3c** illustrates both cumulative and non-cumulative FMD, where a clear Gutenberg–Richter trend is observed at higher magnitudes, while deviations at the lower end indicate a completeness threshold (Mc) near Mw 3.2–3.5. These insights establish the reliability of the dataset for b-value estimation.

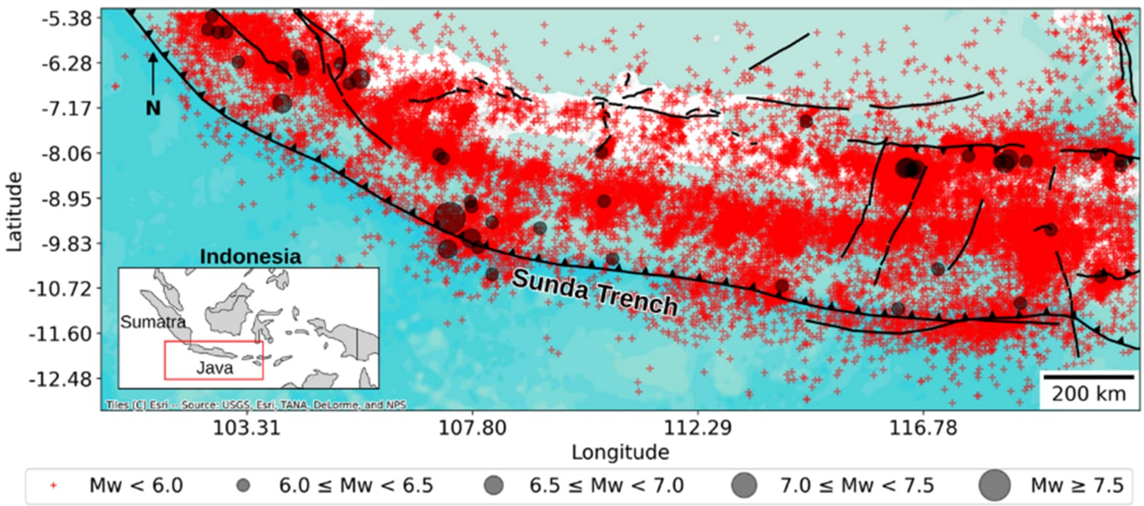

Figure 1. Earthquake distribution across Java and surrounding regions, extending to the Sunda Trench.

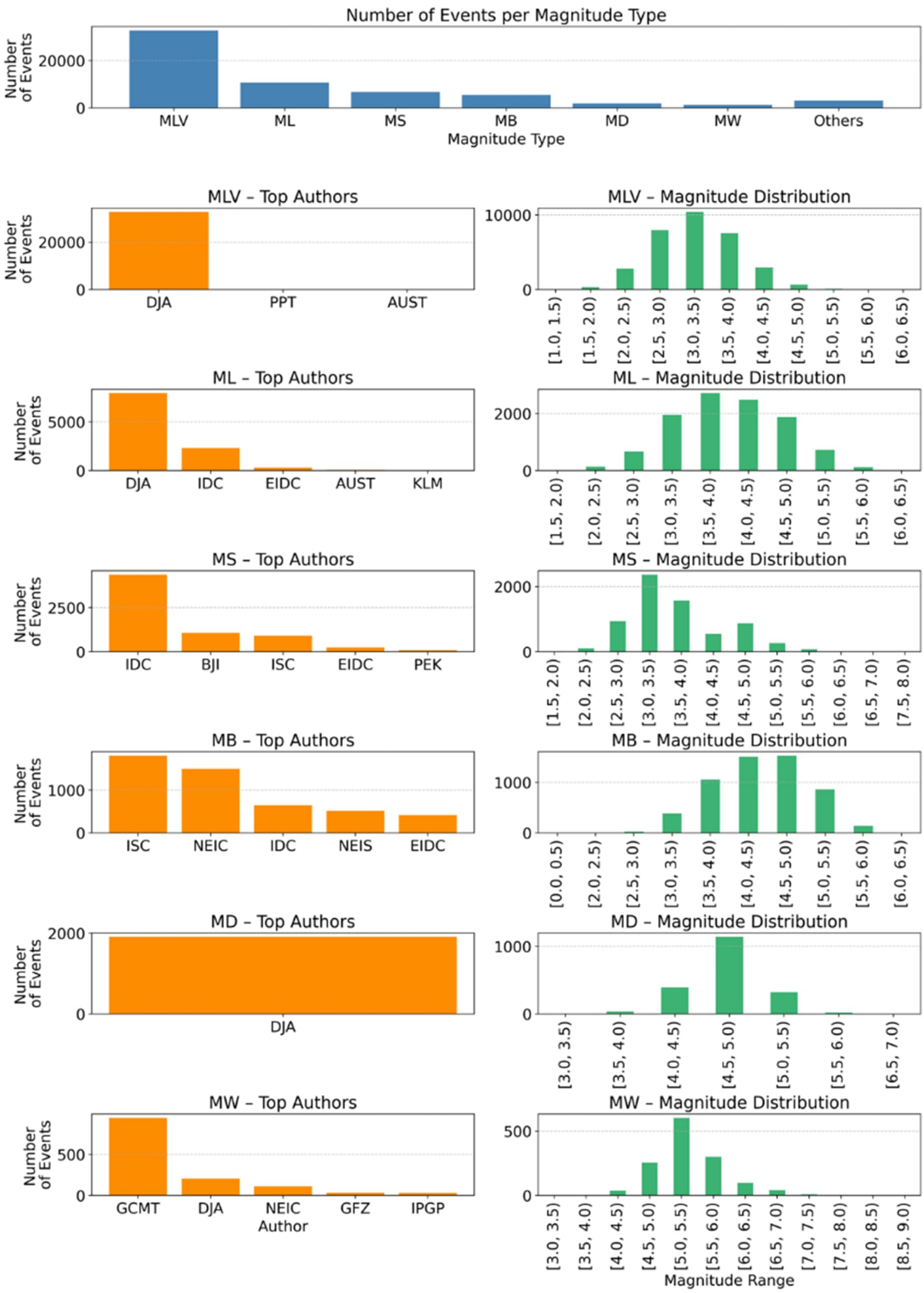

Figure 2. Distribution of initial earthquake events categorized by magnitude type before the conversion, along with distributions by the most contributing authors and magnitude ranges.

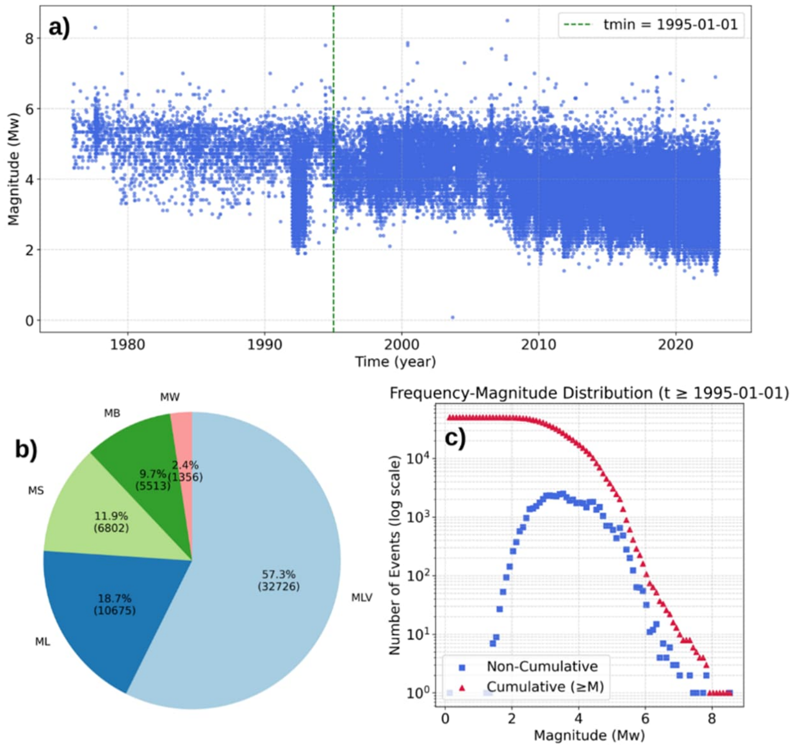

Figure 3. (a) Magnitude versus time plot used to assess catalog completeness using converted moment magnitude (Mw); (b) Pie chart showing the percentage contribution of each magnitude type used in the Mw conversion; (c) Cumulative and non-cumulative distributions of earthquake event counts as a function of converted Mw, using data from 1995 onward.

The spatial modelling of b-values was carried out using the OK1993 model applied to Voronoi cells generated from Sobol-distributed partitions. **Figure 4a** presents the BIC scores across thousands of tested models, where the best-fitting 100 models were selected to construct a robust ensemble. **Figure 4b** displays the fit of the OK1993 model to observed probability density of data in a representative cell, demonstrating strong agreement between empirical and theoretical distributions. **Figure 4c** illustrates the spatial configuration of the Voronoi tessellation, which captures the heterogeneous nature of seismic clustering and enables localized estimation of b-values. These model-driven insights reveal the spatial variation of seismic behaviour across the region.

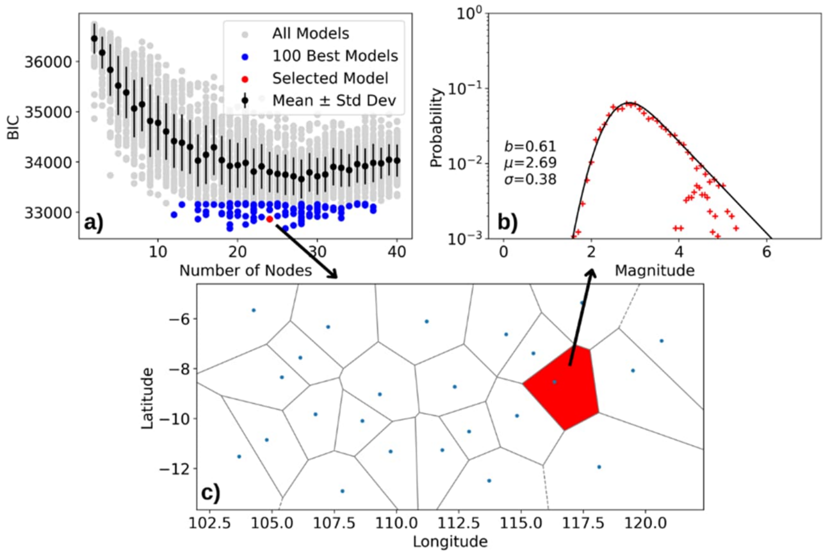

Figure 4. (a) BIC values for all generated models (gray), the top 100 selected models (blue), and the specific model shown in subfigure (c) (red); (b) Probability density of earthquake events by magnitude, along with the theoretical curve fitted from the selected cell in subfigure (c); (c) Voronoi model representation.

4.2. Spatial Distribution of b-values, Uncertainty, and Implications

Figure 5 reveals significant spatial variability in b-values across Java and surrounding regions, highlighting key seismotectonic contrasts. In panel (a), high b-values (b > 1.2) are concentrated in southwest Lampung and south of Bali, while low b-values (b < 0.8) dominate the Sunda Strait, northern Java, Lombok, Sumbawa, and parts of Sumba—areas. Moderate b-values (b = 0.8–1.0) form a relatively continuous band along the southern coast and offshore Java. Panel (b) shows that regions with low Median Absolute Deviation (MAD), such as southern Java and Bali, have stable b-value estimates, whereas higher MAD values in sparsely populated or offshore areas indicate greater uncertainty due to limited data. Panel (c) confirms that well-sampled cells yield more reliable estimates especially along the Java Trench and major population centers, while cells with fewer contributing models align with zones of low seismicity and require cautious interpretation.

To enhance the robustness of interpretation, **Figure 6** presents the spatial distribution of median b-values after applying quality filters based on MAD(b) < 0.5 and N(b) > 80. This filtering criterion ensures that only b-value estimates with high statistical stability (low dispersion) and sufficient sampling (event-rich cells) are visualized. The white regions in the map represent cells excluded due to high uncertainty or insufficient data. By focusing on stable zones, the filtered map allows more confident inferences about tectonic segmentation and seismogenic behavior.

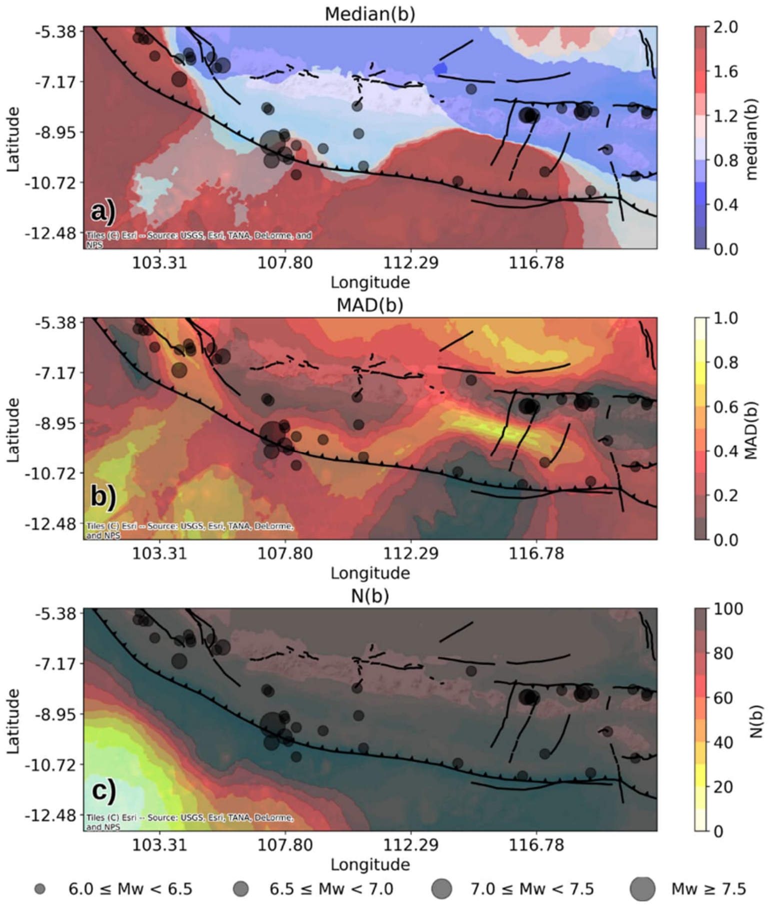

Figure 5. (a) Spatial distribution of median *b*-values from the top 100 selected models; (b) Distribution of MAD (Median Absolute Deviation) values; (c) Distribution of the number of *b*-values used to compute the median and MAD in each cell (some cells in certain models may lack *b*-values due to insufficient data). Events with magnitudes greater than Mw 6.0 are represented by black circles.

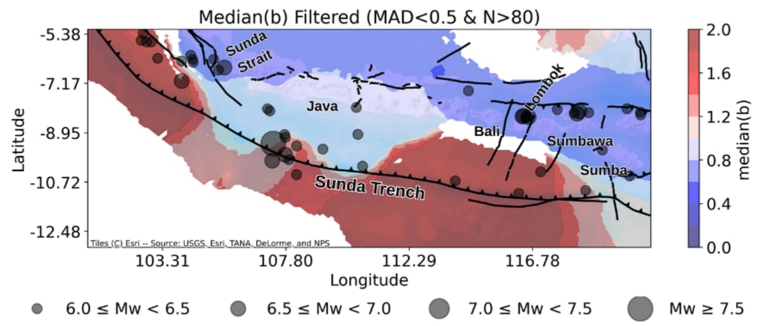

Figure 6. Spatial distribution of median b-values from the top 100 selected models after filtered by MAD(b) < 0.5 and N(b) > 80. The white color on the map represents median b-values outside the filter parameters.

The spatial variability of b-values across Java and surrounding areas thus provides insight into regional seismotectonic segmentation. Zones with high b-values (b > 1.2), such as southwest of Lampung and south of Bali, may indicate areas dominated by small-magnitude seismicity and heterogeneous crust which represents weakly coupled zones. In contrast, low b-values (b < 0.8) observed in segments of the Sumatra fault system near the Sunda Strait, inland faults across Java, and thrust faults north of Bali, Lombok, and Sumbawa likely correspond to asperities or zones of stress concentration and mechanical locking (Scholz, 2015; Schorlemmer & Wiemer, 2005). These patterns may pose seismic hazards comparable to those from the megathrust.

A prominent pattern is the continuous zone of moderate b-values (b = 0.8–1.0) along the southern Java trench—from West to East Java—reflecting a potentially transitional seismic behaviour. This segment may be partially coupled, not fully creeping nor completely locked, and could represent an area of mixed rupture potential. Compared to the higher b-value zones in southwest Lampung and south of Bali, the southern Java trench appears relatively more locked.

This observation raises the possibility that portions of the southern Java megathrust, particularly offshore Central and East Java, may represent seismic gap candidates—segments that have not experienced large-magnitude ruptures in recent decades despite accumulating strain (Kelleher et al., 1973; McCann et al., 1979). However, confirmation of this hypothesis requires additional constraints, such as geodetic strain rates, historical rupture data, or slip deficit analysis.

When compared to previous studies that used conventional grid-based methods, the results of this study show several improvements. For example, Rahayu and Madrinovella (2024) analyzed b-values in the Yogyakarta region using a fixed 1.5 × 1.5 km grid and a 15 km radius. Their results revealed low b-values (0.35–0.75) particularly near the Opak and Ngalang faults, indicating high stress accumulation. However, the use of fixed radius and grid spacing, while achieving high resolution, makes the estimates sensitive to local data availability and may exaggerate small-scale variability. Moreover, their comparison between different grid sizes showed inconsistencies driven by the smoothing effect of larger radii (e.g., 3 × 3 km grid with 45 km radius), emphasizing the methodological bias inherent in parameter choices.

Arubi et al. (2022) applied a Fixed Mc method with 0.1° × 0.1° grid spacing across Java and reported that b-values ranged from 0.6 to 2.6, with the Java megathrust averaging 1.19 ± 0.20. Although the wide range of values reflects large-scale variability, fixed gridding likely contributed to artificial discontinuities, especially near the boundaries of data-rich and data-poor regions. Similarly, Arimuko et al. (2023) identified low b-value zones in western Java's subduction interface, indicating seismic gap potential.

In contrast, the present study adopts a fully data-driven, adaptive spatial partitioning approach using Voronoi tessellation with Sobol-distributed seeds, combined with estimation of b-value via the OK1993 model. The ensemble filtering strategy (e.g., via MAD and cell number thresholds) further reduces the risk of overinterpretation in poorly constrained regions. As a result, this approach captures both regional-scale trends and fine-scale heterogeneities with greater statistical confidence and spatial consistency, while minimizing the influence of arbitrary parameter settings.

While these spatial b-value patterns align with known tectonic features and highlight the importance of data-driven modelling approaches in identifying megathrust segmentation, the use of Sobol-based spatial sampling provides uniform node coverage, minimizing sampling bias compared to traditional Voronoi or grid methods. Additionally, the OK1993 formulation improves robustness in regions with heterogeneous event completeness.

Overall, the results confirm the effectiveness of the Voronoi–OK1993 ensemble modelling approach. This methodology not only captures meaningful spatial heterogeneity but also ensures interpretability by emphasizing statistically robust estimates. Compared to conventional gridded approaches, this study offers improved resolution without sacrificing stability, making it a valuable tool for seismic hazard modelling in the tectonically complex Java region.

5. CONCLUSION

This study applied a Voronoi-based ensemble modelling framework combined with the OK1993 formulation and Sobol-distributed spatial sampling to estimate the spatial distribution of Gutenberg–Richter b-values in Java and its surrounding regions. The results show a clear segmentation pattern, with high b-values (b > 1.2) in southwest Lampung and south of Bali, moderate values (b = 0.8–1.0) along the southern Java trench, and low values (b < 0.8) in the Sunda Strait, northern Java, and parts of the Nusa Tenggara islands. Notably, low b-value zones also cover active fault systems inland and offshore, highlighting their potential seismic hazard. The ensemble approach offers improved spatial stability, while the Sobol sequence ensures uniform sampling coverage.

This modelling framework provides a more objective alternative to conventional grid-based approaches, especially in data-heterogeneous regions. However, limitations remain, such as the assumption of spatial uniformity within each Voronoi cell and the sensitivity to magnitude conversion and initial parameter estimation. Future developments may incorporate temporal changes in b-value and extend the analysis to include slip deficit and rupture history. These improvements could help identify locked segments and potential seismic gaps with greater confidence, supporting more refined seismic hazard assessments in subduction-prone regions like Java.

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