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Revealing Spatial Variations of Earthquake Stress Drop and Peak Ground Acceleration Using a Non-Ergodic Modeling Framework

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Key Points:

- We retrieve robust spatial repeatable patterns from stress drop and ground motion data sets of small earthquakes in the Bay Area
- A strong spatial correlation between stress drop and peak ground acceleration is unveiled by non-ergodic Gaussian Process regression
- Our extracted non-ergodic stress drop can represent regional source effects in ground motion, thus improving ground motion model prediction

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Improving accuracy and reducing uncertainty in ground motion models (GMMs) are crucial for the safe design of infrastructure. Traditional GMMs often oversimplify source complexity, such as stress drop, due to high variability in estimation. This study aims to address this issue by extracting robust spatial variations in stress drop estimates and ground motion residuals. We introduce a non-ergodic modeling framework using Bayesian Gaussian Process regression to analyze data from over 5,000 earthquakes (M2-4.5) in the San Francisco Bay area. Our findings reveal consistent spatial patterns in non-ergodic stress drop and peak ground acceleration (PGA), providing a reliable approach to understanding the spatial distribution of stress drop and its link to regional tectonics. Furthermore, integrating source models derived from the non-ergodic stress drop into GMMs can effectively account for source effect in ground motions and reduce aleatory uncertainty. This study establishes a framework for utilizing stress drop data sets to enhance seismic hazard assessment.

Plain Language Summary Ground shaking is the primary cause of damage during earthquakes, making accurate predictions vital for designing safer buildings. However, traditional models used to predict ground shaking often oversimplify the complex nature of earthquake sources, which may impact the uncertainty of seismic hazard analysis. In this study, we aim to improve source characteristics in ground motions by focusing on a key factor, stress drop, which has a significant influence on ground shaking but is known for its high variability due to measurement methods. To address this, we apply Gaussian Process regression to extract consistent patterns from the highly variable stress drop data before eventually incorporating it into the ground motion model. We analyze data from over 5,000 small earthquakes in the San Francisco Bay area. The extracted repeatable regional stress drop values presented in this study reveal underlying regional tectonic patterns. Additionally, we demonstrate that incorporating these extracted stress drop values reduces the variability in ground motion predictions without adding uncertainty from stress drop estimations. This serves as a potential bridge between stress drop and ground motion data sets, ultimately enhancing seismic hazard analysis and preparedness by leveraging stress drop insights.

1. Introduction

Earthquake ground motion is controlled by three factors: the earthquake source, the traveling path of seismic waves, and local site conditions. These factors are incorporated into Ground Motion Models (GMMs), which play a crucial role in assessing and mitigating seismic hazard and risk. Modern GMMs have improved in accuracy by introducing detailed parametrizations of the path and site effects (Douglas & Edwards, 2016), such as basin amplifications (Abrahamson et al., 2014; Campbell & Bozorgnia, 2014) and site-specific responses informed by regional geology (Thompson et al., 2011). However, the earthquake source effect remains less thoroughly explored, with source complexity often being simplified or neglected in practical GMM implementations (Chatterjee et al., 2023; Wald, 2020). The spectral stress drop, also known as the stress parameter in earthquake engineering, is such an example despite of its critical role in driving ground motion (Atkinson & Beresnev, 1997; Baltay & Hanks, 2014; Baltay et al., 2013; Hanks & McGuire, 1981; R. K. McGuire & Hanks, 1980; Yenier & Atkinson, 2014). Over the years, significant efforts have been made to expand stress drop data sets, particularly in regions like California (Goebel et al., 2015; Hardebeck & Aron, 2009; Jones & Helmberger, 1996; Shearer et al., 2006; Trugman & Shearer, 2018). Additionally, community-led improvements in methodology and data set refinement have enhanced the reliability and utility of stress drop measurements (Abercrombie, 2021; Baltay et al., 2013, 2024; Ji et al., 2022; J. J. McGuire & Kaneko, 2018; Shearer et al., 2022; Shimmoto & Miyake, 2024).

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These advantages provide an opportunity to better characterize earthquake source effects and use stress drop data set to enhance ground motion modeling, especially where high-quality ground motion data is sparse.

One of the primary challenges in incorporating estimated stress drop into ground motion prediction is the high variability associated with seismological stress drop estimations. This variability arises from factors such as corner frequency measurements (Abercrombie et al., 2021; Shearer et al., 2019, 2022; Trugman & Shearer, 2017) and dynamic rupture model selection (Kaneko & Shearer, 2014, 2015; Wang & Day, 2017). Stress drop variability is often reported 3–4 times greater than the variability in the between-event residuals of GMMs (Cotton et al., 2013), which quantify event-specific deviations between observed ground motion and the median GMM predictions. Despite these uncertainties, relative stress drop values are effective in capturing meaningful spatial and temporal variations that provide insights into fault behavior and earthquake interactions (Chaves et al., 2020; Hardebeck & Aron, 2009; Kaneko & Shearer, 2014; Ruhl et al., 2016; Shearer et al., 2022). It has been extensively reported (e.g., Ameri et al., 2017; Baltay et al., 2013, 2017, 2019; Chatterjee et al., 2024; Oth et al., 2017; Trugman & Shearer, 2018) that global and regional variations in stress drop have strong correlations with the between-event residuals, suggesting that regional stress drop trends may contribute to improved ground motion modeling. However, evaluated regional variations by methods such as manually grouping events in different regions (Ameri et al., 2017; Chiou et al., 2010; Oth et al., 2017) and average neighboring data (Baltay et al., 2017) may introduce subjectiveness in grouping and ignore intra-group differential characteristics and inherent multi-scale spatial correlation in data (Cressie, 2015).

To effectively capture reliable spatial variations in stress drop and integrate them into the GMMs, it is essential to first reduce their variability, produce clear and continuous spatial patterns, and account for spatial correlations with ground motion source terms. Inspired by the widely applied non-ergodic ground motion modeling framework (e.g., Abrahamson et al., 2019; Kuehn & Abrahamson, 2020; Lacour, 2023; Lavrentiadis & Abrahamson, 2023; Lavrentiadis et al., 2023; Macedo & Liu, 2022; Sung et al., 2023), which breaks the ergodic assumption equating global variability with local variability, we are aimed for extracting repeatable regional patterns that contribute to median ground motions, also known as epistemic term in Baltay et al. (2017). This approach decomposes epistemic uncertainty as more data and knowledge are gathered (Der Kiureghian & Ditlevsen, 2009) from the aleatory uncertainty (a random scattering effect that cannot be reduced solely by increasing data volume), thus achieving the reduction of the modeling uncertainty. We recognize that this framework is not only advantageous for GMMs, but also highly effective for extracting consistent spatial information from the diverse stress drop data sets. Several methods have been proposed to incorporate non-ergodic terms in ground motion modeling to capture continuous spatial patterns, including Kriging interpolation (Sung & Lee, 2019), geographically weighted regression (Caramenti et al., 2022) and Gaussian Process regression (GP, Lavrentiadis et al., 2023). In this study, we apply GP regression to stress drop data sets to identify spatial patterns and extend the same approach to peak ground acceleration (PGA) data sets to analyze their correlations. The selection of GP over other methods will be detailed in the Methodology section. This method is ideal for revealing regional or fault-based relationships between the processed non-ergodic data sets. GP methods have also been adopted in other source-related studies; for instance, using the GP approach on high-frequency ground motions during earthquakes reveals a strong link between fault complexity and source effects that influence high-frequency ground motions in Southern California (Chatterjee et al., 2024).

We conduct GP-based non-ergodic analyses on a data set from Trugman and Shearer (2018), which includes calibrated stress drops and peak ground accelerations (PGA) from over 5,000 earthquakes (M2 to 4.5) in the San Francisco Bay area. These events span several major faults, including the San Andreas, Hayward, Rodgers Creek, Maacama, and Calaveras faults (Figure 1). While previous research has demonstrated a strong correlation between stress drop and between-event variability in PGA, our study advances this understanding by producing spatially repeatable patterns in stress drop using a non-ergodic framework. Our goal is to clarify the relationship between these spatial patterns and verify a reliable stress drop data set to be included accounting for the non-ergodic source effect in GMM predictions for future events.

2. Methodology and Data Processing

In this study, we perform GP-based non-ergodic analyses on the stress drop and PGA data sets from Trugman and Shearer (2018). The non-ergodic modeling is performed over the deviations from the median back-bone models

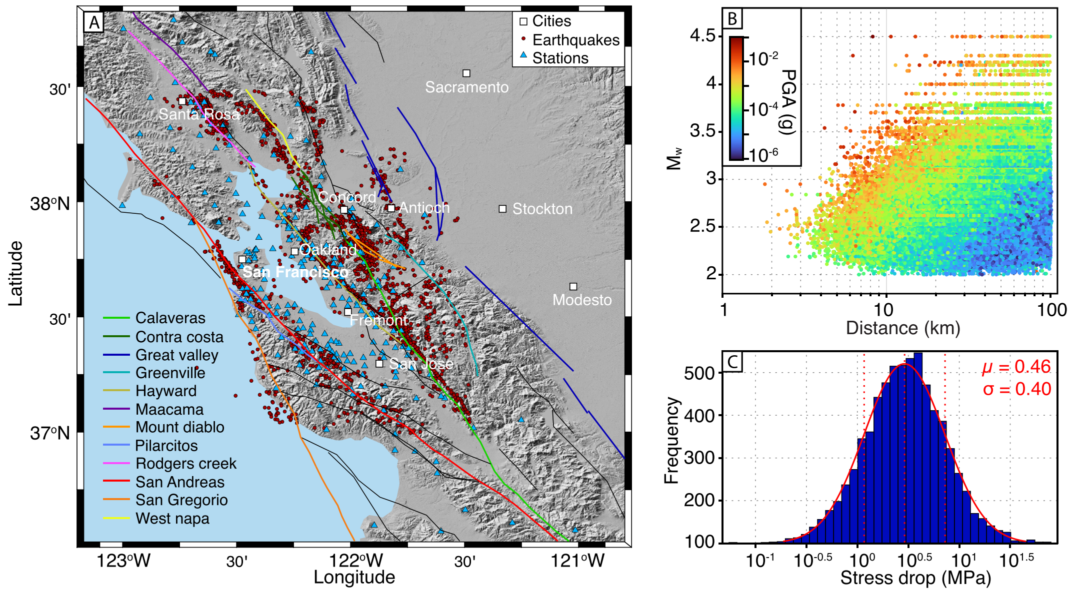

Figure 1. Data used in this study. (a) Map view of San Francisco Bay Area study region with fault traces from the Uniform California Earthquake Rupture Forecast, Version 3 (Field et al., 2014). Squares, triangles and circles represent major cities, stations and earthquake epicenters, respectively. (b) Distribution of PGA with respect to source-site distance and magnitude. (c) Histogram of stress drops of the earthquakes. The Red solid line is the best-fitting normal distribution with the mean of 0.46 ($\log_{10}$ MPa) and the standard deviation of 0.40. Red dashed lines indicate the values of mean and mean ± standard deviation.

of the stress drop and between-event term of PGA. Details of developing the back-bone models for residual analyses are described in the supplement (Text S1 and Figure S1 in Supporting Information S1).

The non-ergodic modeling extracts spatially varying but repeatable characteristics from the aleatory source-specific terms, represented as the relative stress drop $\Delta B\sigma_i$ (stress drop of each earthquake minus global average) and the between-event PGA residual ΔB_i with i representing the ith earthquake. The relative stress drops are decomposed into three components in Equation 1:

$$\Delta B\sigma_i = \delta c_0 + \delta c_e(\mathbf{x}_e) + \delta B\sigma_i \tag{1}$$

where δc_0 is a systematic offset, δc_e represents the regional repeatable stress drop variation as a function of location (hereafter called the non-ergodic stress drop for simplicity). δc_e will be positive if events within a specific region tend to have larger stress drops than the global average. $\delta B\sigma_i$ is the stress drop residual after non-ergodic modeling. The PGA between-event residuals are similarly decomposed into three components:

$$\Delta B_i = \delta d_0 + \delta d_e(\mathbf{x}_e) + \delta B_i \tag{2}$$

where δd_0 is a systematic offset, and δd_e represents repeatable location-specific adjustments to the median ground motion. This term thus represents regional ground motion variability conditioned on event location ($\mathbf{x}_e$). For simplicity, we refer to this term as the source term of PGA. The remaining component, δB_i, is the non-ergodic between-event residual.

In this study, non-ergodic terms of $\delta c_e(\mathbf{x}_e)$ and $\delta d_e(\mathbf{x}_e)$ are developed as Varying Coefficient Models (VCM), which employ smooth spatial kernel functions to account for the spatial correlations identified in the data. This approach addresses limitations of traditional methods, such as direct neighboring averaging or manual clustering/grouping, which can introduce subjectivity and fail to capture finer data characteristics. Generally, spatial variable modeling presents challenges due to the large number of coefficients required for estimation, especially when considering a grid-based approach in a big area. The spatial correlation structure in VCMs helps to mitigate this challenge. Among the available non-ergodic modeling approaches, the GP offers distinct advantages for spatial modeling. GP regression operates within a probabilistic framework, offering both a mean prediction and an uncertainty estimate, which is important for reliable decision-making in regions with sparse or uncertain data. GP uses a flexible covariance function to automatically learn spatial relationships, capturing complex, non-linear dependencies effectively (Lavrentiadis et al., 2023). This flexibility reduces the need for predefined models and manual parameter tuning, making GPs more adaptable to varying data structures (Heaton et al., 2019; Rasmussen, 2003). Furthermore, GP has seen widespread application in machine learning, where its capability to generalize and handle non-linearity makes them a powerful tool for geospatial data analysis (Liu et al., 2020; Rasmussen & Nickisch, 2010).

Specifically in this study, GP regression treats model coefficients as random variables following normal distributions and determines their spatial distributions through mean and covariance functions controlled by hyperparameters. For example, it can determine whether a coefficient remains constant over a domain, varies continuously over a finite length scale, or is spatially independent. This reduces the computational cost, as only the hyperparameters require estimation. This approach has been applied in non-ergodic ground motions models (e.g., Macedo & Liu, 2022; Meng et al., 2023; Meng & Goulet, 2023; Sung et al., 2024). Here, δc_e and δd_e are modeled as the Gaussian Processes with a zero mean and Matérn covariance matrix, controlled by an exponential kernel function (Lavrentiadis et al., 2023):

$$k(\mathbf{x}_m, \mathbf{x}_n) = \omega^2 \exp\left(\frac{-\|\mathbf{x}_m - \mathbf{x}_n\|}{l^2}\right) \quad (3)$$

where $\mathbf{x}_m$ and $\mathbf{x}_n$ represent two events coordinates, and hyperparameters ω and l govern the standard deviation and spatial length scale of the coefficients. The term $\|x_m - x_n\|$ corresponds to the distance between two events. For the non-ergodic terms of $\delta B\sigma_i$ and δB_i in Equations 1 and 2 can be also modeled as GP but with an identity kernel function which is given by:

$$k(\mathbf{x}_m, \mathbf{x}_n) = \omega^2 \delta(m - n) \quad (4)$$

where $\delta(m - n)$ is the Dirac delta function. It assumes that the source-specific contributions are statistically independent and hold a zero-centered normal distribution with ω as the standard deviation. The GP regressions are performed using a R-package: Integrated Nested Laplace Approximation (INLA, Rue et al., 2009). Through INLA, a Bayesian framework estimates these hyperparameters allowing δc_e and δd_e to be modeled as Bayesian ensembles that capture medians and spreads.

3. Results

In this study, a non-ergodic analysis of stress drop is performed using spatial discretization across the study area, with PGA between-event residuals processed to validate the non-ergodic stress drop. These non-ergodic terms are first modeled at mesh nodes (Figure S2 in Supporting Information S1) and then projected back onto their original event locations (Figure 2) for residual analysis. We use a 15 km mesh size, as both finer (5 km) and coarser (40 km) meshes produce consistent spatial patterns. This indicates that the spatial pattern extracted by our approach is independent of mesh resolution. Our new approach significantly decreases the variability in stress drop to 0.56 (standard deviation in natural logarithm), only 61% of the variability in the raw stress drop data set (Figure S3 in Supporting Information S1). It is fairly close to those of inferred stress drops from observed PGA between-event variabilities (see Table 1 in Cotton et al., 2013). The Pearson correlation between non-ergodic stress drop and PGA and terms (0.64) shows a slight improvement over the correlation between PGA between-event residuals and stress drop (0.58). Additionally, non-ergodic stress drop and PGA terms exhibit clear and consistent spatial patterns across the study area (Figure 2), offering enhanced delineation of regional variations compared to directly visualizing PGA between-event residuals and stress drop (Figure 4 in Trugman & Shearer, 2018). This result provides strong evidence that the extracted regional stress drop pattern is robust and can effectively evaluate source-relevant ground motion variability for future events, potentially paving the way for incorporating stress drop information into GMMs.

On a large scale, many events in the southwestern area (including the San Andreas and San Gregorio faults) exhibit higher PGA and stress drop than those in the northeastern area (including the Calaveras, Greenville, and

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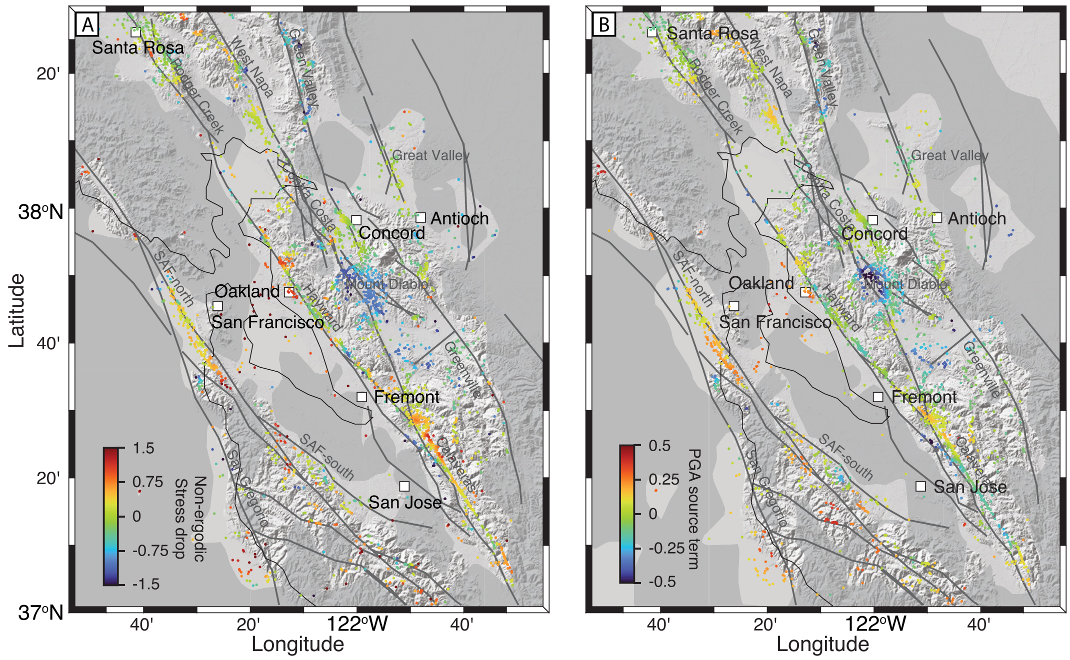

Figure 2. Spatial distribution of the non-ergodic stress drop source term (a) and the non-ergodic PGA source term (b). Dot colors represent median values, with white background areas indicating regions where both terms are comparably credible (standard deviations below 0.6 for non-ergodic stress drop and 0.2 for PGA source term). Detailed distributions of standard deviations of these two fields are illustrated in Figure S4 in Supporting Information S1. Fault names are labeled in gray.

Great Valley faults). Locally, events near the junctions of the Calaveras and Hayward faults show high PGA and stress drop. A similar pattern is observed near the junction of the San Andreas and San Gregorio faults, suggesting that events near the junctions of major faults are likely to release more stress and generate stronger ground motions. This observation is important for seismic hazard analysis and resilient infrastructure design in San Francisco, Fremont, and San Jose. Conversely, events near the Mount Diablo region exhibit regionally low values for both PGA and stress drop. These observations showcase the consistency in regional variations of non-ergodic stress drop and PGA source terms (Figure 2). However, unique regional characteristics may lead to deviations from consistency. For instance, events around the central Hayward fault (near Oakland) show anomalously high stress drop but average PGA levels, possibly due to unique fault behaviors (Hardebeck & Aron, 2009), fault geometry (Lee et al., 2024), or systematic biases in the estimation of these quantities.

A notable advantage of this approach is its capability to provide spatially varying uncertainty for each estimated term, thereby offering a nuanced understanding of model credibility across different regions. As illustrated in Figure 2, the levels of uncertainty are predominantly influenced by the availability and density of data points (Figure S4 in Supporting Information S1). Areas with abundant data show lower uncertainty, reflecting greater confidence in the model predictions. This spatial uncertainty assessment is especially valuable when we interpret relative stress drop for a specific event from our developed regional stress drop map, as it highlights the robustness and reliability of the results, particularly in regions with uneven or sparse data coverage.

4. Discussion

In this study, the VCM non-ergodic analysis framework is employed to investigate regional variabilities and interconnections between spectral stress drop and PGA. Events near major faults are grouped to examine regional or fault-specific variations in correlations between PGA and stress drop fields, as shown in Figure 3. Unlike the diffuse, clouded distribution observed in the PGA between-event residuals and stress drop, as shown in (Figures 3b–3e), the non-ergodic terms in Figures 3c and 3e reveal distinct localized striped patterns, significantly enhancing correlations between local stress drop and PGA. For example, the correlation in the Calaveras-central group increases from 0.6 in a clouded pattern to 0.9 in a striped pattern (Figures 3f and 3g). More complex

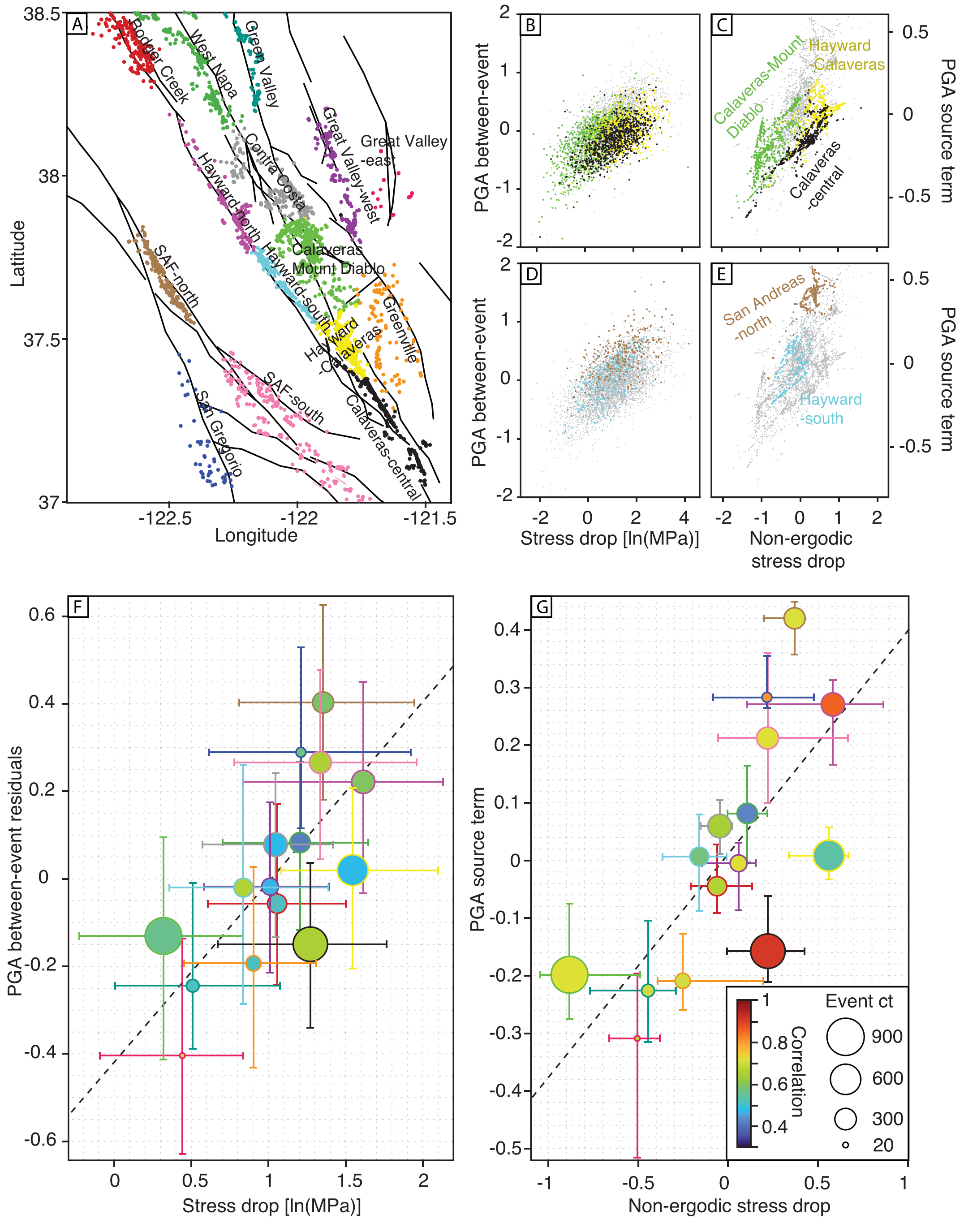

Figure 3. Regional correlation analysis of PGA and stress drop. (a) Events are grouped by their nearest major faults. (b), (d), and (f) show correlations between PGA between-event residuals and stress drop, while (c), (e), and (g) show correlations between the PGA source term and non-ergodic stress drop. In panels (b) through (e), gray dots represent the global database. In panels (f) and (g), circles represent event groups, indicating median values with uncertainty bars (25th and 75th percentiles). Circle filling color and size denote the correlation coefficient and the number of events, respectively, edge color labels the groups in panel (a). Dashed lines in (f) and (g) are the average global scalings.

patterns, such as multiple stripes and a combination of stripes and clouds, are observed in the other fault groups (Figures 3c and 3e), suggesting the underlying fault complexity in these regions (Trugman & Shearer, 2018).

The non-ergodic stress drop and PGA measures from different fault groups exhibit reduced group-specific uncertainties compared to those derived from PGA between-event residuals and stress drop (Figures 3f and 3g), increasing confidence in interpreting them in relation to fault characteristics. For instance, groups such as West Napa, Contra Costa, Hayward-south, Great Valley-west, and Rodger Creek exhibit stress drop and ground motion within the average regime. High stress-drop groups, supported by elevated PGA source terms, include SAF-north, SAF-south, San Gregorio, and Hayward-north, indicating potentially increased regional seismic hazards. Conversely, low stress-drop groups include Calaveras-Mount Diablo, Green Valley, Greenville, and Great Valley-east. However, certain fault segments notably deviate from the average scaling, as indicated by the dashed lines in Figures 3f and 3g, which may indicate connections to source complexity:

1. The **Hayward-Calaveras** segment (yellow) near fault junction shows a sufficient number of events characterized by larger stress drops without elevated ground motions (Figures 2 and 3g). This aligns with the complex faulting environment at the junction of the Hayward and Calaveras faults, where fault termination, jump-over, and interconnection typically involve higher stress accumulation and higher fault damage (Mia et al., 2024; Perrin et al., 2016; Powers & Jordan, 2010; Wang & Day, 2020; Wang & Goulet, 2021) and potentially lead to larger stress drop (Hecker et al., 2010; Moyer et al., 2018; Perrin et al., 2021; Ross et al., 2018).

2. The **SAF-north** (brown) group also shows elevated stress drop potentially due to the merging of two major faults, where events are enclosed by the San Andreas fault, the San Gregorio fault, and the Pilarcitos fault. Unlike events in the Hayward-Calaveras junction system, these events exhibit anomalously high ground motion, significantly deviating from the average scaling line (Figure 3g). The 1906 M7.7 San Francisco earthquake, which was likely initiated in this area (Lomax, 2008), further suggests the high regional seismic hazard. The discrepancy in events near fault junctions may arise due to the properties of the involved faults: the San Andreas fault and the Pilarcitos fault are more seismically active and have a larger differential in long-term slip rates (15–25 mm/year for the SAF and 0–3 mm/year for the Pilarcitos fault, respectively). In contrast, the Hayward and Calaveras faults have a much smaller difference in slip rates (10–20 mm/year for the Hayward fault and 5–15 mm/year for the Calaveras fault, respectively) (Field et al., 2014).

3. In contrast, events in the **Calaveras-central** (black) group exhibit lower ground motion and average stress drop (Figures 2 and 3g). This is likely related to the surface-creeping central Calaveras fault, which has a relatively high interseismic slip rate ($> \sim 10$ mm/year) (Chaussard et al., 2015) and a low coupling ratio (Galehouse & Lienkaemper, 2003). These observations imply that earthquakes on creeping faults may produce different characteristic ground motions, such as reduced high-frequency contents, which aligns with the theoretical understanding that velocity-strengthening friction penalizes fast-propagating ruptures (e.g., Harris, 2017; Lozos et al., 2015; Quin, 1990). However, Harris and Abrahamson (2014) reported that 11 of the largest recent earthquakes on shallow creeping faults in tectonically active continental regions did not produce peak ground motions noticeably different from those generated by similar-magnitude earthquakes on locked faults. This disagreement may be due to previously limited ground motion records and neglect of regional variations in ground motions. Our approach, therefore, introduces new perspectives into seismic hazards associated with creeping faults, complementing physics-based modeling efforts (Harris et al., 2021; Noda & Lapusta, 2013).

This study introduces an alternative approach to examining stress drop properties using non-ergodic stress drop terms as well as the corresponding ground motion. Previous studies have reported depth dependence of stress drop, helping to better understand earthquake rupture mechanics (Abercrombie, 2021; Abercrombie et al., 2021). In this study, both stress drop and ground motion slightly increase with depth down to 10 km and then remain roughly constant to 22 km (Figures 4a and 4b). This observation supports the idea that earthquakes may exhibit depth-variable characteristics, such as depth-dependent normal stress (Byerlee & Brace, 1968) or frictional properties (Dieterich, 1979; Nie & Barbot, 2021, 2024). Such depth dependence may also arise from uncorrected source-depth-dependent attenuation, as highlighted by Abercrombie et al. (2021). Additionally, to assess whether earthquake sources are scale-invariant or if smaller earthquakes differ systematically from larger ones (Abercrombie, 2021; Shearer et al., 2022), we analyze the dependence of estimated stress drop and its non-ergodic stress drop term with respect to magnitude (Figure 4c). Stress drop shows a slight increase with magnitude (Trugman & Shearer, 2018), which is also observed in Southern California (Shearer et al., 2019, 2022). However, the non-ergodic stress drop shows no noticeable magnitude dependence. The PGA between-event residual decreases with magnitude (opposing the stress drop dependence in Figure 4d), whereas the PGA source term remains magnitude-independent.

The earthquake self-similarity hypothesis (constant stress drop regardless of magnitude, Aki, 1967; Kanamori & Anderson, 1975; Prieto et al., 2004) suggests that stress drops estimated from small events can be extrapolated to

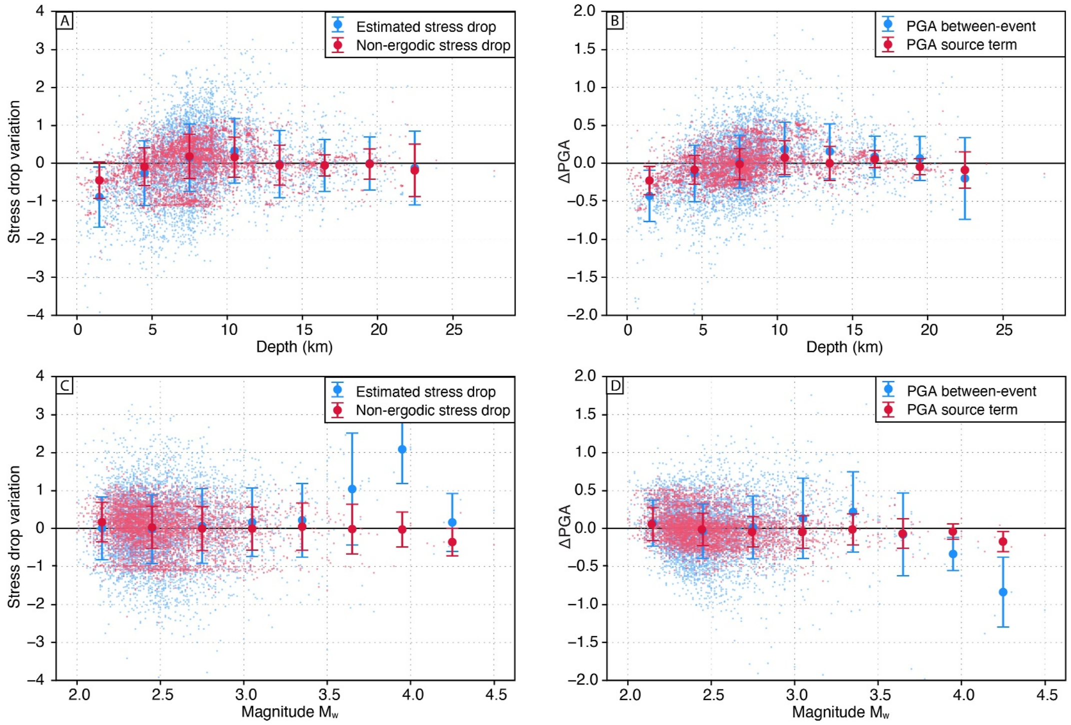

Figure 4. Depth dependence of stress drop (a) and PGA (b), and magnitude dependence of stress drop (c) and PGA (d). Blue circles and bars represent the median and standard deviation of estimated stress drop variations (i.e., estimated values minus the global average on a natural logarithm scale) or PGA between-event residuals within each depth and magnitude bin. Red circles and bars represent the median and standard deviation of non-ergodic stress drop or PGA source terms within each depth and magnitude bin.

larger earthquakes, which is supported by the non-ergodic stress drop and PGA in this study (Figures 4c and 4d). However, the applicability of such observations to large-magnitude events is still an ongoing discussion (Parker et al., 2023). Hardebeck (2020) found that stress drops from small earthquakes do not reliably predict the stress drops of nearby moderate-to-large earthquakes. Trugman (2022) argued that this discrepancy might be partly due to the vast methodological differences and large measurement uncertainties of historical studies compiled in the meta-analysis, in addition to the limited records of large events. Similarly, Chiou et al. (2010) observed that regional ground motion differences between southern and central California diminish for larger events ($M > 6$), implying that regional trends derived from small-to-moderate events may not always scale to larger magnitudes. This may be due to the scarcity of ground motion data for large earthquakes. Our approach aims to extract regional trends from highly variable data, potentially contributing to resolving this issue. In Figure S5 in Supporting Information S1, we examine whether the spatial variations in the stress drop non-ergodic component and PGA source term are independent of magnitude. We find that the spatial patterns generally hold across different magnitude bins (2−2.5, 2.5− 3, and >3); however, due to sparse data for larger events ($M > 3$), it is inconclusive whether the same spatial patterns apply to larger magnitudes. While these magnitudes are too small to fully address the magnitude extrapolation question, applying our new non-ergodic analysis over larger areas with a broader magnitude range may further clarify this issue.

In this study, we aim to explore how the extensive existing stress-drop data set can be utilized to account for source effects in ground motion, ultimately contributing to the development of a stress-drop-informed ground motion model (GMM). Stress drop estimates, particularly those derived from spectral analysis, are often highly variable due to differences in methodologies and data selections (Abercrombie, 2021; Baltay et al., 2024). However, progress has been made as the stress drop community continues to enhance measurement reliability by addressing site and path effects and refining the source spectral shape (Abercrombie et al., 2021; Bindi et al., 2023a, 2023b; Shearer et al., 2022; Shimmoto & Miyake, 2024). For example, some stress drop estimation approaches (e.g., Baltay et al., 2013, 2019; Shimmoto & Miyake, 2024) have progressed to narrow the variability gap between estimated stress drop and high-frequency ground motion source terms (Sung et al., 2024) or between-event residuals (Campbell & Bozorgnia, 2014; Cotton et al., 2013; Oth et al., 2017; Rodriguez-Marek et al., 2011). Our approach builds upon these improved stress drop measurements and we acknowledge that epistemic uncertainty associated with stress drop processes from different groups still exists. However, it manages to reduce uncorrelated aleatory uncertainty in estimations by extracting repeatable spatial patterns. As a result, the variability of the non-ergodic stress drop is reduced by nearly 61% compared to original estimates and nearly achieves inferred variability levels consistent with those of high-frequency ground motion as shown in (Cotton et al., 2013). It is important to note that the spectral stress drop, or stress parameter, generally measures the strength of high-frequency seismic radiation relative to the moment and may not necessarily relate to differential stresses on the fault (Atkinson & Beresnev, 1997). The specific physical source model used to interpret source spectra—whether it assumes a circular crack, pulse-like rupture, unilateral rupture, varying rupture velocity, or complex rupture geometry (Kaneko & Shearer, 2014, 2015; Lin & Lapusta, 2018; Wang & Day, 2017) can introduce uncertainty into the estimation of real mechanical stress drop on fault; however, it does not alter the earthquake source radiation spectra that matters to ground motion. Therefore, the uncertainty related to model selection is less relevant to our goal of assessing the ground motion source effect. Despite uncertainties in absolute stress drop measurements, the extracted spatial characteristics in this study are generally robust, as relative measurements are less sensitive than the absolute values to methodological differences (Kaneko & Shearer, 2014; Shearer et al., 2022). The spatial patterns of stress drop identified in this study are further supported by the observed high-frequency ground motion source effects, as shown in Figure 2 and Figure S2 in Supporting Information S1. To evaluate the generality of these findings, future work should focus on testing the robustness of the extracted spatial characteristics using multiple stress drop data sets targeting the same event list and waveforms, such as the Ridgecrest stress drop results compiled by Baltay et al. (2024).

Incorporating stress drop into GMMs, instead of relying solely on source-specific ground motion residuals, offers several benefits. Ground motion and stress drop data are typically derived through different approaches. Compared to decomposed source effect in ground motion data (Abrahamson & Youngs, 1992) that may be biased by the trade-off with regional path effect (Baltay et al., 2020), the process of obtaining stress drop focuses specifically on isolating source effect by comprehensively addressing in situ path and site effects. It includes considerations of 3D velocity structure and depth-dependent path correction (Abercrombie, 2021; Abercrombie et al., 2021; Bindi et al., 2023b). Furthermore, stress drop data sets have been systematically accumulated over the past couple of decades, particularly in California (Hardebeck & Aron, 2009; Shearer et al., 2006, 2022). Besides, incorporating stress drop into GMMs improves predictive resolution by refining source-term modeling and facilitates the modeling of source effects in regions with limited ground motion data, akin to how parameters such as Vs30 (average shear wave speed in top 30 m) and basin depth are used to quantify site effects across wide areas. Additionally, while stress drop correlates with PGA between-event residuals (Baltay et al., 2013; Hanks & McGuire, 1981; Oth et al., 2017; Trugman & Shearer, 2018), individual event measurements lack the repeatability necessary for direct application in GMM development because individual earthquakes are inherently non-repeatable. Instead, the regional non-ergodic stress drop derived in this study provides a stable, regional or fault-based trend that can be applied to future events, offering a robust framework for integrating source effects into GMMs.

To illustrate how non-ergodic stress drop can serve as an independent source characteristic and enhance ground motion predictions, we use the data set provided as a DesignSafe ground motion data set as an example (Ji et al., 2023). This data set, which primarily documents ground motions in California, includes more earthquakes than NGA-West2 and was processed separately from the ground motion data set used in this study. Although the data set contains 82 earthquakes of $M < 5$ within the study region, it is insufficient for developing a VCM-based source model and lacks accurate stress drop measurements. Following the workflow in Figure S6 in Supporting Information S1 (details provided in Text S2 in Supporting Information S1), we develop non-ergodic stress drop values for the events in the DesignSafe data set. We find that these non-ergodic stress drop values correlate with PGA and high-frequency spectral accelerations (SAs) with periods shorter than 0.5 s, with correlation coefficients exceeding 0.3 (generally a strong correlation in ground motion modeling). Incorporating a simple linear scaling of the non-ergodic stress drop can reduce the between-event residual variability for PGA and high-frequency SAs by 5%–10%. In contrast, no significant correlation or reduction in variability is observed for low-frequency SAs or PGV, which is consistent with the findings of Chatterjee et al. (2024). This highlights the potential of bridging two independently derived datasets—stress drop and ground motion. When ground motion data is insufficient to develop a non-ergodic source term, utilizing a spatially variable non-ergodic stress drop map derived from seismological estimates offers a viable approach to represent regional source effects and reduce between-event residuals effectively.

Using data from small earthquakes in the Bay Area, we have developed a non-ergodic modeling framework to reassess the relationship between stress drop and ground motion intensity. Different approaches have been used by various research groups to estimate stress drop (Baltay et al., 2024), some studies are for the same region (e.g., Hardebeck & Aron, 2009). Future work should explore the consistency of our results using different stress drop catalogs or in other regions, such as in Southern California (Chatterjee et al., 2024; Shearer et al., 2022). To develop a more comprehensive stress drop-informed ground motion model, it is essential to examine the relationships between stress drop and other ground motion intensity measures, including long- and short-period SAs, similar to the work of Chatterjee et al. (2024). Additionally, future efforts should focus on collecting various ground motion intensities from databases like the recent DesignSafe database (Ji et al., 2023) and integrating stress drop estimates obtained through multiple seismological methods (e.g., Baltay et al., 2019; Macias et al., 2008).

5. Conclusions

This study presents a non-ergodic framework that reveals a significant relationship between the spectral stress drop and the GMM source term. By analyzing over 5,000 small earthquakes in the San Francisco Bay area, we demonstrate that accounting for consistent spatial variability in these parameters provides a robust method for understanding the spatial distribution of highly variable stress drop and its connection to the regional tectonic environment. Additionally, this approach provides regional, non-ergodic, map-based stress drop information that can be feasibly applied to predict source effects for future earthquakes. The framework proposed in this study enables the effective use of existing stress drop data to enhance the accuracy and reliability of seismic hazard assessments, supporting more informed earthquake preparedness and risk mitigation efforts.

Data Availability Statement

The data used in this study are sourced from Trugman and Shearer (2018). The non-ergodic framework was constructed using the R-INLA software (Rue et al., 2009), an R package designed for approximate Bayesian inference for Latent Gaussian Models. The R-INLA software is available at https://www.r-inla.org/.

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