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Data-Driven Seismic Hazard Zonation of Indonesia to Support SDG 11 Using DBSCAN and K-Means Clustering

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ABSTRACT

Objective: To examine ten years of earthquake data recorded across Indonesia drawing on 5,364 events with magnitudes above M 5.0 between 2016 and 2025. **Method:** DBSCAN algorithm was run after the optimal neighborhood radius was determined objectively from a k -distance plot. An elbow at about 65 km was identified and the value yielded 16 spatially distinct clusters alongside 460 noise events. **K-means** algorithm identified four seismic regimes. **Results:** Of the four regimes, one cluster (Cluster 1) concentrated every major earthquake in the catalog (64 events with $M \geq 7.0$), even though it accounted for fewer than one event in ten. The three remaining clusters captured background seismicity at near-identical mean magnitudes of approximately from 5.33 to 5.35. At the conventional zonal level, Maluku-Sulawesi generated the most events about 40.8% from total events, while Sumatra registered the highest seismic energy output. A Gutenberg-Richter b -value of 0.98 was estimated for the full catalog. **Novelty:** Introducing earthquake zonation methods based on machine learning for earthquake catalog of Indonesia. These findings support multiple Sustainable Development Goals including the identification of underestimated high-energy rupture corridors informs evidence-based urban risk reduction (SDG 11), strengthens the scientific foundation for earthquake disaster preparedness (SDG 13), introduces an innovative and reproducible machine learning methodology applicable to infrastructure (SDG 9), and contributes a freely transferable workflow that adopt data-driven zonation methods (SDG 17).

INTRODUCTION

The 2004 Sumatra-Andaman rupture reached M_w 9.1-9.3 and set off a tsunami that killed more than 200,000 people across fourteen countries (Sarkawi et al., 2024). The 2009 Padang earthquake (M_w 7.6) caused widespread structural collapse across West Sumatra (Kadir et al., 2024; Natawidjaja & Triyoso, 2007). In 2018, the Palu earthquake and liquefaction disaster demonstrated that even moderate-length fault segments can trigger catastrophic cascading failures when soil conditions and coastal geometry conspire against a population (Cilia et al., 2022; Heidarzadeh & Mulia, 2023). These repeated earthquake phenomena share a common thread including communities and infrastructure. They were exposed to levels of ground shaking that hazard assessments had either underestimated or communicated inadequately to those responsible for land-use planning and building codes (Iuchi et al., 2023; Stein & Wyssession, 2003). Conventional seismic hazard zonation addresses this problem by dividing a study region into geographic provinces that estimate earthquake recurrence within each province and translating those estimates into design ground motions. The approach is well-established and has produced the national seismic hazard map of Indonesia (PusGen, 2017). However, its limitation is that zone boundaries are drawn by experts exercising professional judgment, and there is no guarantee that those boundaries correctly capture the underlying structure of seismicity.