

A CAUSAL LENS PERSPECTIVE ON BASIN EFFECTS

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Keywords: Causal Inference, Basin Effects, Structural Damage, Double Machine Learning

Introduction

Earthquakes pose a significant threat to the safety and well-being of a large portion of the global population. As the rate of urbanization continues to exceed the rate of population growth, the risks associated with seismic hazards intensify, especially in urban areas where vertical expansion through high-rise structures is often the solution to housing demands. These tall structures are particularly susceptible to damage and collapse during earthquake events due to amplification and prolonged ground shaking. These phenomena are exacerbated in sedimentary basins, where two- and three-dimensional seismic wave propagation mechanisms significantly alter ground motion intensity, spectral content, and duration. Despite decades of research, basin effects remain inadequately understood and are often oversimplified in current seismic hazard assessment frameworks.

The effects of sedimentary basins have been observed in several major earthquakes, where damage was concentrated in urban centres built over deep sedimentary deposits. For instance, during the 1985 Michoacán earthquake (M8.1), Mexico City experienced catastrophic damage to tall buildings due to basin-induced amplification (Pilz et al., 2011; Assimaki et al. 2012). A similar pattern of damage was observed in the Seattle basin during the 2001 Nisqually earthquake (M6.8), and in Christchurch, New Zealand, during the Canterbury Earthquake sequence (2010 M7.1 Darfield and 2011 M6.3 Christchurch events).

Methodology

Our research focuses on two key domains: ground motion characterization and structural response/damage assessment. For ground motion characterization, we consider multiple intensity measures (IMs), such as spectral acceleration, peak ground acceleration, Arias intensity, and significant duration, which collectively capture the amplitude, frequency content, and duration of ground shaking. The study employs both empirical data from past earthquakes and simulated ground motions using advanced nonlinear models. This dual approach ensures that our findings are robust and applicable across a range of seismic scenarios.

The structural response and damage assessment component investigates the performance of tall buildings and critical infrastructure within basins under real and simulated ground motion records. Using causal machine learning, we disentangle the effects of basin amplification, ground motion duration, and other confounding factors (e.g., spectral shape, pulse effects) on structural damage metrics. This approach enables us to establish causal relationships rather than mere associations, thereby providing actionable insights for engineering design and policy decisions. The proposed work represents a paradigm shift in how sedimentary basin effects are studied and incorporated into seismic risk assessments. By leveraging causal inference, we move beyond traditional statistical methods to explicitly address the challenges posed by confounding variables. This transition is crucial for developing scientifically rigorous and practically relevant models that can inform effective risk mitigation strategies. We formulate our causal problem as basin/non-basin as treatment, vs30, basin depth, Magnitude, focal depth, geology of site as confounders where PSAs are outcomes. We employ Propensity score methods such as and Double machine learning approach to quantify and explore

factors contributing to basin effects. The propensity score is calculated using logistic regression or more advanced methods such as machine learning models. This score represents the likelihood of treatment assignment based on observed covariates (Rosenbaum & Rubin, 1983). Individuals in the treatment group are matched with those in the control group based on similar propensity scores, reducing bias due to confounding variables (Austin, 2011). Double machine learning (DML) (Bach et al. 2021) is a statistical method designed to estimate causal effects in high-dimensional settings by leveraging machine learning models. It is particularly useful for constructing unbiased treatment effect estimates from observational data, even when dealing with complex covariates. Preliminary results from our research indicate that causal machine learning methods, such as causal forests and double machine learning, can effectively isolate the effects of individual basin features. The figure 1 below shows a preliminary DAG (Direct Acyclic Graph) to conceptualize both the causal and statistical dependencies between the variables that are considered in seismic intensity and infrastructure damage assessments. The unmeasured influences on Basin Geomorphology (BA), PGA and M are denoted as U_{BA} , U_{PGA} and U_M .

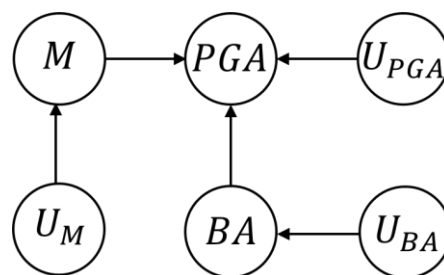


Figure 1. Simple 3-variable DAG where the goal is to isolate the causal effect of BA on PGA

Looking ahead, the insights gained from this research have the potential to significantly improve the accuracy of seismic hazard models and enhance our understanding of infrastructure vulnerability in basins. By explicitly quantifying the causal effects of basin geomorphology, we aim to bridge the gap between seismology and structural engineering, fostering a more holistic approach to seismic risk mitigation.

Conclusion

In conclusion, this study underscores the importance of interdisciplinary research in addressing complex challenges at the intersection of earth sciences and engineering. The integration of causal inference into seismic hazard and risk assessments marks a critical step toward more resilient urban infrastructure in earthquake-prone regions. We believe that the findings from this research will not only advance scientific understanding but also contribute to the development of evidence-based policies and practices that prioritize safety and sustainability.

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