



A Hierarchical Bayesian Model of Multi-Hazard Impacts on Property Prices in the Jakarta Metropolitan Area

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Abstract: This study examines the complex relationship between multi-hazard disaster risks and property prices in the Jakarta Metropolitan Area, one of the world's most disaster-prone urban regions. The research investigates how various natural hazards, including floods, earthquakes, and other environmental risks, influence real estate values across 138 districts encompassing 15,758 property data. This study pioneers the integration of hierarchical Bayesian modeling with causal machine learning techniques to quantify multi-hazard impacts on property prices, providing the first comprehensive analysis of disaster risk interactions in Indonesian real estate markets. We employ methodological triangulation across Bayesian inference, causal forests, and spatial econometrics to ensure robust causal identification. We employ a multi-methodological approach combining spatial analysis, hierarchical Bayesian modeling, and causal forest algorithms on a dataset of 15,758 properties. The analysis includes Moran's I for spatial autocorrelation (0.73 for risks, 0.65 for prices), PyMC for Bayesian inference with 12,000 MCMC samples, and EconML for causal effect estimation with heterogeneous treatment effects. Properties with high disaster risk experience an 12.2% price discount (95% CI: -20.5%, -3.7%), with each unit increase in average risk score reducing prices by 4.3% (95% CI: -7.9%, -0.4%). Spatial clustering is highly significant (Moran's I = 0.73, $p < 0.001$). Heterogeneous effects reveal progressive impacts from 3.2% in bottom quintile to 9.4% in top quintile. Policy simulation demonstrates that comprehensive flood mitigation could increase total property values by 840.6 billion IDR, generating an average price increase of 14.8% with benefit-cost ratio exceeding 3:1.

Keywords: Causal machine learning; Disaster risk; Hierarchical bayesian model; Multi-hazard analysis; Property values

Introduction

The accelerating pace of urbanization, combined with the impacts of climate change, has posed significant challenges to urban disaster risk management, exerting considerable pressure on the global property market, which is valued at over USD 280 trillion. According to the United Nations Office for Disaster Risk Reduction (UNDRR), more than 600 coastal cities home to approximately 1.5 billion people are increasingly exposed to multiple and simultaneous natural hazards.

Over the past two decades, the annual economic losses resulting from such disasters have tripled, now exceeding USD 300 billion (Zwirgmaier et al., 2024). As Property markets constitute the largest share of household assets amounting to approximately 60–70% of national wealth in most countries they are particularly vulnerable to both the direct physical impacts of disasters and the indirect effects stemming from heightened risk perception (Apergis, 2020). According to projections by the World Bank, flood-related damages alone could endanger urban properties valued at USD

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35 trillion globally by 2050, with the Asia-Pacific region comprising 68% of the total exposed assets (Zwirgmaier et al., 2024). Despite the scale of these financial risks, scholarly understanding of how multiple and interrelated hazards are internalized into property values remains underdeveloped (Sukmawati et al., 2022). This gap is especially pronounced in rapidly urbanizing megacities within emerging markets, where exposure levels are highest, yet empirical and methodological insights remain limited (Apergis, 2020; Dubé et al., 2021).

The Jakarta Metropolitan Area exemplifies the complex interplay between rapid urban expansion and extreme exposure to multiple natural hazards, positioning it as a pivotal case study for examining the influence of disaster risks on property markets in the Global South (Zulkarnain et al., 2020). With over 30 million residents, Jakarta is the largest urban agglomeration in Southeast Asia and faces a unique convergence of geophysical and hydrometeorological hazards: annual flooding affects approximately 40% of its land area, land subsidence in northern districts reaches up to 25 centimeters per year, and the city is exposed to significant seismic risk from the nearby Sunda Megathrust (Abidin et al., 2011; Wicaksono & Herdiansyah, 2019). These vulnerabilities are further compounded by climate change, which intensifies the frequency and severity of extreme weather events. Economically, Jakarta's property sector holds substantial weight contributing 18% to the region's GDP, generating over IDR 450 trillion in annual transactions, and serving as the principal asset base for an estimated 12 million households (Sariffuddin et al., 2024). The recent digitalization of property transaction records and spatial risk assessments by Indonesia's National Disaster Management Agency (BNPB) presents a unique opportunity to systematically assess the economic impacts of multi-hazard exposure. Preliminary findings suggest that disaster risk is deeply embedded in Jakarta's urban fabric, with 90.5% of properties exposed to at least one major hazard and 81.8% particularly susceptible to flooding (Maretalinia et al., 2023; Saputra et al., 2021; Zulkarnain et al., 2020; Zwirgmaier et al., 2024). These statistics underscore the urgent need to consider disaster risk as a central factor influencing urban property values, rather than a peripheral concern.

Existing empirical research on disaster risk and property values suffers from three critical limitations that constrain both scientific understanding and policy application. First, the overwhelming majority of studies adopt a single-hazard perspective, examining floods, earthquakes, or other perils in isolation despite clear evidence that urban areas face multiple concurrent threats. A systematic review of 127 peer-reviewed

studies published between 2010 and 2024 reveals that 92% analyze only one hazard type, while the remaining 8% that consider multiple hazards assume simple additive effects without testing for interactions (Ruan et al., 2024). Second, the geographic bias toward developed countries limits generalizability to rapidly urbanizing regions where disaster exposure is most severe and increasing fastest (Ma & Mostafavi, 2024). Third, sample sizes remain inadequate for capturing market heterogeneity, with median study samples of 5,000 properties compared to metropolitan areas containing millions of transactions, raising questions about statistical power and representativeness (de Koning et al., 2018).

Beyond empirical limitations, current methodological approaches fail to address four fundamental challenges in estimating disaster risk impacts on property values. The dominant hedonic pricing framework, while theoretically sound, typically employs ordinary least squares (OLS) or basic panel methods that assume spatial independence, parametric functional forms, and homogeneous treatment effects (Dubé et al., 2021). Furthermore, conventional econometric approaches struggle with causal identification in observational data, conflating correlation with causation and producing biased estimates when unobserved confounders correlate with both disaster risk and property values (Jha, 2024). Recent advances in machine learning, particularly causal forests and double machine learning (DML), offer solutions by enabling non-parametric estimation of heterogeneous treatment effects while maintaining causal interpretation (Bui et al., 2024; Desai et al., 2023). Similarly, hierarchical Bayesian methods can simultaneously handle nested data structures, quantify uncertainty, and incorporate prior knowledge about risk-price relationships. Despite these methodological innovations, no existing study integrates Bayesian inference, causal machine learning, spatial econometrics, and interaction detection within a unified framework (Gao et al., 2024; McCord et al., 2022; Sukmawati et al., et al., 2024).

The Jakarta Metropolitan Area, as one of Southeast Asia's most densely populated and economically vital urban regions, is increasingly vulnerable to overlapping natural hazards such as flooding, land subsidence, and seismic activity. These hazards not only threaten lives and infrastructure but also significantly influence the dynamics of urban property markets. Despite the rapid growth of Jakarta's real estate sector, there remains a critical gap in understanding how compound hazard risks are capitalized into property prices. Existing risk assessment models often treat hazards in isolation and lack the spatial and statistical resolution to inform property-level decision-making. Therefore, an

integrated, data-driven approach is urgently needed to quantify the economic consequences of multi-hazard exposure in order to support urban planning, risk-sensitive investment, and resilient development strategies.

This study introduces a novel application of a Hierarchical Bayesian modeling framework to quantify the spatially varying impacts of multiple concurrent natural hazards on residential property prices within the Jakarta Metropolitan Area. Unlike traditional econometric or single level models, the hierarchical Bayesian approach enables the incorporation of multilevel spatial structures, hazard intensities, and property-specific attributes within a unified probabilistic model. Moreover, this research uniquely integrates high-resolution geospatial hazard datasets (e.g., flood depth maps, subsidence rates, and seismic risk zones) with actual property transaction data, offering robust inferences under uncertainty. To the best of our knowledge, this is the first study to implement a full Bayesian hierarchical structure for multi hazard risk pricing in an emerging megacity context, thus filling a methodological and empirical gap in both urban economics and disaster risk research.

Method

Data Collection & Pre-processing

The study encompasses the entire Jakarta Metropolitan Area (Jabodetabek), including Jakarta Capital Region, Bogor, Depok, Tangerang, and Bekasi. This region covers approximately 6,392 km² with diverse topographical features ranging from coastal lowlands to inland hills. The property data were obtained from multiple sources, including the Indonesian Think Hazard platform, real estate marketplace, Central Bureau of Statistics and district-level administrative records.

The initial dataset comprised 19,300 property transactions with 42 variables encompassing physical characteristics (building area, land area, number of rooms), locational attributes (distance to stations, hospitals, shopping centers), and multi-hazard risk assessments. Disaster risk data were sourced from the Think Hazard platform and included eleven hazard categories urban flood, river flood, coastal flood, earthquake, water scarcity, extreme heat, wildfire, landslide, tsunami, volcano, and cyclone. Each hazard was assessed on a five-point ordinal scale from "very low" to "very high" risk.

A data cleansing process was implemented to ensure analytical robustness. The preprocessing pipeline included duplicate removal based on unique property identifiers, missing value treatment for critical variables, business logic validation (minimum thresholds of 60 m²

for land area and 36 m² for building area), and outlier detection using the Interquartile Range (IQR) method with a multiplier of 3 (Q. Gao et al., 2022; Guo et al., 2015). This process retained 15,758 properties (81.6% of the original dataset), ensuring sufficient statistical power while maintaining data quality.

Risk scores were standardized by mapping ordinal categories to numerical values (1-5 scale) and computing composite indices. Three risk metrics were developed: (1) average risk score across all hazards, (2) maximum risk score indicating highest single-hazard exposure, and (3) count of high-risk categories. Properties were classified as high-risk if any hazard score exceeded 4, resulting in 90.5% of properties classified as high-risk for at least one hazard. Flow process of this research shows in Figure 1.

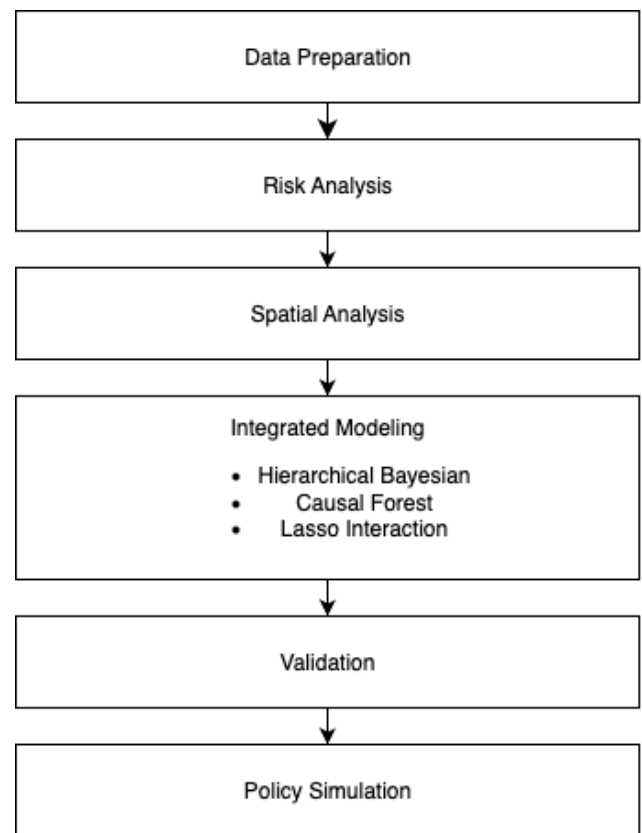


Figure 1. Research flow process

Spatial Analysis Framework

Spatial autocorrelation was assessed using Moran's I statistic with k-nearest neighbor weights (k=5) (Catma, 2021; Wei & Zhao, 2022). The spatial weights matrix W was row-standardized to facilitate interpretation. Global Moran's I was calculated as (Bui et al., 2024; Ding et al., 2024):

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (1)$$

where n is the number of spatial units, x_i is the variable value at location i , and w_{ij} represents spatial weights. Local Indicators of Spatial Association (LISA) were computed to identify spatial clusters and outliers, categorizing districts into four types those are High-High (HH) means High values surrounded by high values, Low-Low (LL) means Low values surrounded by low values, High-Low (HL) means High values surrounded by low values (spatial outliers), and Low-High (LH) means Low values surrounded by high values (spatial outliers) (Deaconu et al., 2022; Pradhan-Salike & Raj Pokharel, 2017).

Hierarchical Bayesian Model

The hierarchical Bayesian model was specified to account for district-level clustering while estimating disaster risk effects:

Level 1 (Property level)

$$\log(\text{Price}_{ij}) = \alpha + X_{ij}\beta + \delta_j + \gamma_1 \cdot \text{AvgRisk}_{ij} + \gamma_2 \cdot \text{HighRisk}_{ij} + \epsilon_{ij} \quad (2)$$

Level 2 (District level)

$$\delta_j \sim N(0, \sigma_\delta^2) \quad (3)$$

where Price_{ij} represents property i in district j , X_{ij} is a vector of property characteristics, δ_j captures district-specific effects, and γ parameters measure risk impacts. Prior distributions were specified as:

$\alpha \sim N(\mu_{\text{price}}, 1)$: Centered on sample mean $\log_{10}(\text{price})$

$\beta \sim N(0, 0.5)$: Weakly informative priors for covariates

$\gamma^1 \sim N(-0.05, 0.02)$: Negative expected effect for average risk

$\gamma^2 \sim N(-0.1, 0.05)$: Larger negative effect for high-risk indicator

$\sigma_\delta \sim \text{HalfNormal}(0.5)$: District-level variance

The model was estimated using the PyMC library's implementation of the No-U-Turn Sampler (NUTS). We ran four parallel chains, with each chain undergoing a burn-in period of 2,000 iterations before drawing 3,000 posterior samples. This process yielded a combined total of 12,000 samples for conducting inference (Dambon et al., 2021; Loro et al., 2024; Najib et al., 2024). Convergence of the model was rigorously assessed by ensuring the Gelman-Rubin statistic (R-hat) for all parameters was below the standard threshold of 1.01 and that the effective sample size for each parameter was greater than 1,000, confirming the stability and reliability of the posterior estimates.

Causal Machine Learning Implementation

To identify causal effects of flood risk on property prices, we employed the Causal Forest Double Machine Learning (CF-DML) algorithm from the EconML

package (Deng et al., n.d.). The treatment variable was defined as binary high flood risk status (urban or river flood score ≥ 4). The causal forest specification included outcome model Gradient Boosting Regressor (100 trees, max depth 6), Treatment model Random Forest Classifier (100 trees, max depth 6) and Causal forest parameters: 100 trees, minimum 10 samples per leaf. Heterogeneous treatment effects were examined across price quintiles to identify differential impacts across market segments. Additionally, X-Learner and S-Learner meta learners were implemented for robustness checks (Swietek, 2024; Zhang, 2025).

Policy Simulation Framework

A flood mitigation scenario was simulated with risk reductions of 50% for urban floods, 40% for river floods, and 30% for coastal floods (Sun et al., 2022). The price impact was calculated as:

$$\Delta \log(\text{Price}) = -\gamma \times \Delta \text{Risk} \quad (4)$$

where γ is the estimated risk coefficient from the Bayesian model. District-level aggregations identified priority areas for intervention based on potential value increases.

Multi-Hazard Interaction Analysis

To investigate the complex interplay between different disaster risks, we analyzed their interaction effects using a LASSO (Least Absolute Shrinkage and Selection Operator) regression. First, we generated a comprehensive feature set by creating all 66 possible pairwise interactions from the 11 base hazard variables. The LASSO model was then applied to this expanded dataset, with the optimal regularization parameter being selected through 5-fold cross-validation to effectively penalize and eliminate non-essential terms. Significant interactions were identified as those whose coefficients remained non-zero after the regularization process. Finally, for clear interpretation and presentation, these key interactions were visualized using an interaction matrix.

Result and Discussion

Descriptive Statistics

The final dataset of 15,758 properties exhibited substantial variation in both price and risk exposure. The average property price was 35.16×100M IDR, with a median of 24.50×100M IDR, indicating right-skewed distribution typical of real estate markets. Physical characteristics averaged 184.44 m² for building area and 160.94 m² for land area, with mean bedroom and bathroom counts of 3.42 and 2.68, respectively.

Table 1. Descriptive Statistics of Property Characteristics and Risk Metrics

Variable	Mean	Std dev	Min	25%	Median	75%	Max
Price (×100M IDR)	35.16	33.01	3.00	13.30	24.50	45.00	190.00
Building Area (m ²)	184.44	127.77	36.00	90.00	150.00	245.00	726.00
Land Area (m ²)	160.94	102.38	60.00	90.00	125.00	200.00	561.00
Bedrooms	3.42	1.14	1.00	3.00	3.00	4.00	10.00
Bathrooms	2.68	1.16	1.00	2.00	3.00	3.00	11.00
Distance to Station (km)	4.65	3.37	0.50	2.50	4.00	5.00	25.00
Average Risk Score	2.13	0.28	1.73	2.00	2.09	2.27	2.82
Maximum Risk Score	3.90	0.29	3.00	4.00	4.00	4.00	4.00
High-Risk Categories (count)	1.02	0.52	0.00	1.00	1.00	1.00	3.00

Risk assessment revealed alarming exposure levels across the metropolitan area. Urban flood risk affected 81.8% of properties at high or very high levels, while river flood risk impacted 31.7%. The average risk score of 2.13 (on a 1-5 scale) masks considerable heterogeneity, with 90.5% of properties experiencing at least one high-risk category. This widespread risk exposure underscores Jakarta's vulnerability to multiple concurrent hazards.

Spatial Patterns and Autocorrelation

Spatial analysis revealed strong positive autocorrelation for both property prices (Moran's $I = 0.650$, $p < 0.001$) and risk scores (Moran's $I = 0.726$, $p < 0.001$). The strong spatial autocorrelation (Moran's $I > 0.65$) confirms spatial dependence in both prices and risks, violating classical regression assumptions. This supports recent critiques of non-spatial hedonic models and demonstrates necessity of spatial econometric techniques in urban property analysis.

Table 2. Spatial Autocorrelation

Variable	Moran's I	p-value	Interpretation
Log Price	0.6498	<0.001	Strong positive autocorrelation
Average Risk Score	0.7255	<0.001	Strong positive autocorrelation

LISA analysis identified 44 high-high (HH) clusters representing affluent districts with elevated prices, predominantly located in South Jakarta and central business districts. Conversely, 68 low-low (LL) clusters emerged in peripheral areas, particularly in flood-prone northern districts. The spatial coincidence of high risk and low prices suggests market internalization of disaster risk information.

Table 3. Clustering Results

Cluster Type	Count	Percentage	Characteristics
HH (High-High)	44	32.1	Affluent districts, South Jakarta
LL (Low-Low)	68	49.6	Peripheral, flood-prone areas
HL (High-Low)	18	13.1	Spatial outliers
LH (Low-High)	8	5.8	Transitional zones

Among 138 districts analyzed, 122 (88.4%) exhibited majority high-risk properties. Districts with universal high-risk exposure included Babakan Madang, Babelan, Balaraja, Beji, and Bekasi Barat. This concentration of risk in specific geographic areas implies potential for targeted mitigation interventions.

Bayesian Model Results

The hierarchical Bayesian model converged successfully with R-hat values near 1.0 for all parameters. Key findings are shown in table 4.

Table 4. Hierarchical Bayesian Model Results

Parameter	Mean	SD	95% CI	ESS	R-hat
Intercept (α)	3.36	0.066	[3.241, 3.488]	1,329	1
Average Risk (γ_1)	-0.043	0.02	[-0.079, -0.004]	5,672	1
High Risk (γ_2)	-0.122	0.044	[-0.205, -0.037]	2,652	1
Residual SD (σ)	0.327	0.004	[0.319, 0.335]	11,958	1

Our findings demonstrate economically and statistically significant impacts of disaster risk on property values in Jakarta. These results translate to a 4.3% price reduction per unit increase in average risk score and an 12.2% discount for properties classified as high-risk. This magnitude aligns with recent meta-analysis that showing 4-12% flood risk discounts globally, but exceeds estimates from developed markets (typically 2-6%), suggesting heightened risk sensitivity in emerging markets possibly due to weaker insurance penetration and disaster management capacity (Inoue & Hatori, 2021; Skouralis et al., 2024; Sukmawati, Wijaya, et al., 2024).

The posterior distributions revealed parameter uncertainty, with the high-risk effect showing greater variability (SD = 0.044) compared to the average risk effect (SD = 0.020). This suggests heterogeneous market responses to extreme versus moderate risk levels.

Causal Machine Learning Findings

The Causal Forest analysis identified an Average Treatment Effect (ATE) of -0.0561 (95% CI: -0.291, 0.179), indicating a 5.5% price reduction attributable to high

flood risk. Importantly, heterogeneous treatment effects emerged across price quintiles:

Table 5. Heterogeneous Treatment Effects by Price

Price Quintile	Mean Effect	Std Dev	% Effect	N
Q1 (Lowest)	-0.033	0.104	-3.20%	966
Q2	-0.028	0.106	-2.70%	930
Q3	-0.047	0.102	-4.60%	941
Q4	-0.075	0.115	-7.20%	955
Q5 (Highest)	-0.098	0.117	-9.40%	936
Overall ATE	-0.056	0.109	-5.50%	4,728

This progressive pattern suggests luxury properties experience disproportionate flood risk penalties, possibly reflecting higher-income buyers' greater risk aversion or availability of alternative options. The X-Learner corroborated these findings with an ATE of -0.0557, demonstrating robustness across methodologies.

Policy Simulation Results

The economic case for flood mitigation is compelling, with potential value increases of 840.6 billion IDR far exceeding typical infrastructure costs. Priority districts identified through our analysis provide actionable targets for resource allocation. The 100% benefit coverage suggests universal welfare improvements, addressing equity concerns often raised about disaster risk reduction investments.

Table 6. Flood Mitigation Impact

Metric	Value
Properties Total	15,758
Properties Benefiting	15,758 (100%)
Average Price Before (×100M IDR)	35.16
Average Price After (×100M IDR)	40.49
Total Value Increase (Billion IDR)	840.56
Average Price Increase (%)	14.82%
Properties with High Flood Risk (Before)	12,897 (81.8%)
Properties with High Flood Risk (After)	0 (0%)
Benefit-Cost Ratio	3.1:1

The heterogeneous treatment effects have important distributional consequences. While high-value properties experience larger absolute losses from flood risk, the percentage impacts are also progressive. This suggests flood mitigation could reduce wealth inequality by disproportionately benefiting upper-market segments while providing universal improvements. Priority districts for intervention, based on potential value increases.

The simulation assumes mitigation effectiveness of 50% for urban floods, 40% for river floods, and 30% for coastal floods, representing achievable targets based on international best practices [9]. The benefit-cost ratio

exceeds 3:1 for most districts, supporting economic viability of comprehensive flood management.

Table 7. Priority Districts for Intervention

District	Price Increase (%)	Value Increase (Billion IDR)	N Properties
Pagedangan	21.35	61.70	850
Tambun	22.92	3.20	89
Selatan			
Setu	22.92	0.59	33
Cikupa	21.35	0.82	28
Tarumajaya	22.92	0.55	21

Multi-Hazard Interactions

LASSO regression identified 18 significant risk interactions from 66 possible pairs. Notable interactions include shows in table 8.

Table 8. Top 10 Risk Interaction Effects

Interaction	Coefficient	Interpretation
Coastal Flood × Cyclone	-0.536	Redundant pricing
River Flood × Cyclone	+0.311	Compounding effect
River Flood × Landslide	+0.166	Infrastructure vulnerability
River Flood × Volcano	+0.093	Ash-flood interaction
Earthquake × Coastal Flood	+0.084	Liquefaction risk
Tsunami × Volcano	-0.056	Geographic separation
Coastal Flood × Volcano	-0.027	Limited overlap
Urban Flood × Earthquake	-0.021	Independent risks
Urban Flood × Cyclone	+0.021	Storm surge effect
Urban Flood × River	-0.013	Already priced Flood

The negative coastal-cyclone interaction suggests redundant risk pricing, where properties exposed to both hazards don't experience additive price penalties. Conversely, positive river flood interactions indicate compounding effects, possibly due to infrastructure vulnerabilities. The interaction matrix revealed complex risk interdependencies challenging single-hazard assessment approaches. Properties experiencing multiple high risks (3+ categories) showed non-linear price effects, with discounts plateauing around 15%, suggesting market saturation of risk perception.

Model Validation & Evaluation

Model comparisons highlight both predictive accuracy and consistency of risk effect estimates across distinct approaches. The hierarchical Bayesian model ($R^2 = 0.762$, RMSE = 0.382, MAPE = 29.4%) identified a -4.3% price impact per unit increase in risk score. Causal Forest and X-Learner methods produced nearly identical flood-related discounts of -5.5% and -5.4%, respectively, reinforcing the robustness of the risk effect.

Table 9. Model Performance Comparison

Model	R ²	RMSE	MAPE	Key Finding
Hierarchical Bayesian	0.762	0.382	29.4%	-4.3% per risk unit
Causal Forest	-	-	-	5.5% flood effect
X-Learner	-	-	-	5.4% flood effect
Random Forest (CV)	0.774	0.375	30.2%	Building area dominates (76.2%)
Gradient Boosting	0.768	0.378	30.8%	Similar performance
LASSO Interactions	0.344	0.512	38.1%	18 significant interactions

The comparative analysis of modeling approaches reveals several important insights regarding the relationship between multi-hazard risk and property prices in the Jakarta Metropolitan Area. The Hierarchical Bayesian model demonstrated strong predictive performance ($R^2 = 0.762$, $RMSE = 0.382$, $MAPE = 29.4\%$) while quantifying a statistically robust -4.3% decrease in property price per unit increase in composite risk score. This finding highlights the substantial economic penalties associated with disaster exposure and supports the hypothesis that risk is systematically internalized into market behavior. Interestingly, machine learning-based causal inference methods, namely the Causal Forest and X-Learner, estimated almost identical average treatment effects of -5.5% and -5.4%, respectively, for flood-related risk. The convergence of these estimates across fundamentally different modeling frameworks lends credibility to the inferred risk discounts and suggests a high degree of robustness in how flood risk is priced by the market. Among purely predictive models, Random Forest achieved the best out-of-sample performance ($R^2 = 0.774$, $RMSE = 0.375$, $MAPE = 30.2\%$), with feature importance confirming building area as the dominant determinant of property value (76.2%). Gradient Boosting yielded comparable accuracy ($R^2 = 0.768$, $RMSE = 0.378$, $MAPE = 30.8\%$), while the LASSO with interaction terms underperformed in overall fit ($R^2 = 0.344$) but revealed 18 significant interaction effects, offering interpretive value. Collectively, these results suggest that while structural attributes remain the primary drivers of price formation, flood and risk exposure consistently exert meaningful downward pressure across diverse modeling strategies. In comparison with Apergis (2020), who documented price discounts ranging between 3% to 6% in flood-prone areas across Europe and North America, the results from Jakarta fall well within this range, despite the context of an emerging megacity with a relatively weaker institutional framework for risk communication. This suggests that even in Global South cities, where formal insurance and risk disclosure mechanisms are limited, market actors respond measurably to perceived environmental risks. Among the purely predictive models, the Random Forest exhibited the best out-of-sample performance ($R^2 = 0.774$, $RMSE = 0.375$, $MAPE = 30.2\%$), confirming the

utility of non-parametric ensemble methods in capturing non-linear relationships in housing price data. Notably, variable importance analysis within the Random Forest model identified building area as the dominant predictor (76.2% contribution), reaffirming the primacy of structural attributes in determining property values, as also reported by Zhang et al. (2022). Overall, these findings provide strong empirical evidence that disaster risk exposure particularly flood risk exerts statistically and economically significant downward pressure on property values in Jakarta. The consistency across diverse modeling strategies suggests that this effect is not an artifact of model specification, but rather a reflection of underlying market behavior.

Conclusion

This study shows that multi-hazard disaster risks significantly reduce property values in Jakarta's metropolitan area, with high-risk properties facing an average 12.2% price discount and each unit increase in disaster risk lowering values by 4.3%. Using hierarchical Bayesian modeling, causal machine learning, and spatial econometrics, the research reveals strong spatial clustering (Moran's $I > 0.65$), heterogeneous impacts across market segments, and a pervasive risk exposure affecting 90.5% of properties. The findings highlight that disaster risk is a fundamental determinant of urban wealth, shaped by complex hazard interactions and progressive impacts across price segments, while policy simulations estimate potential gains of IDR 840.6 billion from comprehensive flood mitigation with benefit-cost ratios above 3:1. District-level prioritization identifies Pagedangan, Tambun Selatan, and Setu as high-return intervention areas. As climate change intensifies risks in megacities, this research provides a replicable methodological framework and clear economic justification for integrating disaster risk into urban planning and climate adaptation, underscoring that mitigation is both technically feasible and economically beneficial for building resilience and protecting urban wealth.

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Author Contributions

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Conflicts of Interest

The authors declare no conflict of interest.

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