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# Automated Property Valuation with Multi-Hazard Risk: Jakarta Metropolitan Area Study

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**Abstract**

This study crafts a machine learning framework that systematically integrates multi-hazard disaster risk assessments into automated property valuation for the Jakarta Metropolitan Area. The framework addresses 25–30% MAPE typically observed in disaster-prone regions, providing more reliable valuation results. We made 114 prediction features from 42 input variables by using 14,284 property data from Indonesian markets, physical risk data from the Think Hazard platform, and socio-economic data from Central Bureau of Statistics. Elastic Net model performed superior compared to other models which had $R^2 = 0.7922$ and a MAPE of 28.27%. We found that some disaster risks had unexpected beneficial effects on property prices. We expected that risks related to the earth (+40.5%) and water (+19.2%) would have positive effects, while risks related to the weather (-66.9%) would have negative effects. These conflicting results suggest that in complex urban markets, the quality of infrastructure, location premiums, and differences in risk perception may outweigh simple risk penalties. The idea gives realistic ideas for property valuation that takes risks into account, but it also points out big problems with how the market judges how likely a disaster is to happen.

***Keywords:*** *Adaptive Lasso, Disaster Risk Assessment, Feature Engineering, Machine Learning, Property Valuation.*



## 1. INTRODUCTION

Urban growth in many parts of the world is increasingly taking place in areas that are highly exposed to natural hazards [1]. For cities that face recurrent floods, earthquakes, and extreme weather, understanding how disaster risks shape property values has become more than a technical exercise because It is central to planning for resilience and investment security. The Automated Valuation Models (AVMs) have changed how properties are valued in relatively stable markets, by providing fast and scalable assessments [2], [3]. Yet, when applied to hazard-prone environments, these models often struggle. The Error rates that remain within 5–15% in stable common markets can rise to 25–30% in disaster-prone regions, reflecting a fundamental gap in how risks are captured in valuation processes [4], [5], [6].

Indonesia, and some in the Jakarta Metropolitan Area, describes this problem vividly. Located on the Pacific Ring of Fire, the country is highly exposed to earthquakes, volcanic activity, and tsunamis [7], [8], [9], [10], while its capital contends with chronic flooding, severe land subsidence exceeding 10 cm per year in some districts, and intensifying climate extremes [11], [12], [13], [14]. The Cimandiri and Baribis's fault systems have reshaped building codes [10], [15], while annual monsoon floods disrupt daily life and economic activity [13], [16], [17]. With more than 30 million residents, Greater Jakarta is a megacity where geological threats, water-related hazards, and rapid urbanization converge as well as it makes property valuation both urgent and unusually complex [18], [19], [20].

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At the same time, advances in artificial intelligence (AI) and machine learning (ML) are opening new opportunities for property valuation under such conditions [5], [21]. Some research has indicated that machine learning (ML) can outperform conventional regression by identifying nonlinear relationships and spatial heterogeneity [3], [22], [23]. Gao et al. (2022) illustrated the benefits of ensemble models in Sydney's real estate market [24], whereas Deng and Zhang (2025) enhanced accuracy in Hong Kong through explainable AI [25]. Mathotaarachchi et al. (2024) better predictive models for housing data with a lot of different factors [23]. On the disaster side, Yousefi et al. (2020) successfully utilized machine learning for multi-hazard mapping in mountainous areas [26], while Linardos et al. (2022) emphasized the role of machine learning in disaster management through the 3137odelling of intricate risk interactions [27]. Tools such as RiskScape (Paulik et al., 2023) [28] and studies of compound risks reinforce this trend [29], [30]. Other works in urban economics and valuation similarly stress the promise of data-driven modelling [31], [32], [33]. Yet despite these advances, most approaches treat hazards in isolation or apply simplified categories, falling short of integrating multi-hazard frameworks directly into property valuation models [34], [35].

Jakarta provides a compelling case to push this boundary. Property markets here reflect not only hazard exposure but also location premiums, infrastructure quality, and long-standing socio-economic dynamics [20], [36]. In practice, some hazard-prone areas retain high prices because they offer central locations, strong infrastructure, or regulatory safeguards such as stricter building codes [37], [38]. Prior research has even found that disasters can coincide with property premiums, for example in waterfront districts or elevated terrain with attractive amenities [31], [39]. These paradoxes suggest that risk is rarely perceived as a single penalty. Instead, it interacts with desirability in ways that conventional AVMs are ill-equipped to capture [40].

This study responds to that challenge by developing a machine learning framework that systematically integrates multi-hazard risk assessments into automated property valuation for Jakarta. Drawing on 14,284 cleaned property listings, socio-economic indicators, and hazard data from the Think Hazard platform, we transform 42 raw variables into 114 predictive features. This study evaluate with some models including regularized regressions and a new Adaptive Lasso with Risk Prioritization (ALRP) to test how incorporating risk-aware features affects valuation accuracy. Beyond achieving lower error rates, the framework sheds light on how disaster risks intersect with urban property dynamics. It also contributes methodologically and empirically by embedding risk hierarchies into ML optimization as well as showing how markets in a disaster-prone megacity like Jakarta absorb and reinterpret risk. The findings are intended to support more resilient property valuation practices, better-informed investment strategies, and policies that align urban growth with disaster preparedness.

## 2. METHOD

At a conceptual level, the framework brings together three main inputs (property market data, socio-economic indicators, and hazard assessments) into a single process. The data are cleaned, standardized, and transformed through preprocessing and risk quantification, then expanded with feature engineering to capture both market dynamics and disaster risks. These predictors are analyzed using several machine learning models, including the proposed Adaptive Lasso with Risk Prioritization, and the results are evaluated with standard metrics and cross-validation. Figure 1 illustrates the flow of this study.

### 2.1. Data Sources

Our methodological approach utilized three data sources, each providing critical dimensions to our examination of Jakarta Metropolitan Area's property market. We got 19,300 home listings from Indonesia's top real estate websites in October 2024. These listings included detailed information about

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the properties' physical features (land area, building size, room configurations), asking prices, and, location. We got municipality-level metrics from Badan Pusat Statistik Indonesia (BPS) that include population density, household income distributions and amenities.

For our research goals, it was most important that we used standardized disaster risk assessments from the Think Hazard platform. This platform looks at eleven different types of hazards, including geophysical threats (earthquakes, tsunamis, volcanic eruptions), hydrometeorological risks (riverine flooding, coastal inundation, drought), and geomorphological hazards (landslides). This combination of property market data, socio-economic data, and physical risk generated a unique dataset that shows how risk and property values affect each other.

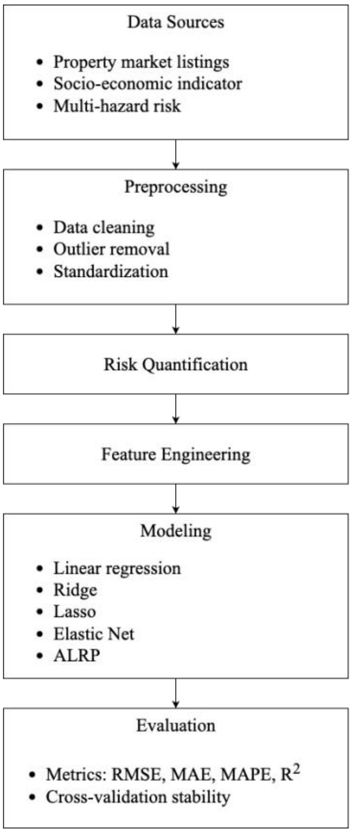


Figure 1. Flowchart of research process

### 2.2. Preprocessing Data

Our initial dataset consisted of 19,300 houses. We conducted cleansing and preprocessed data by removing duplicates, missing values and conduct business judgment to identify unrealistic area-to-price ratios. We used interquartile range methods to removing outlier data and the final data set used for analysis to 14,284 properties.

### 2.3. Risk Quantification and Categorization Framework

Transforming categorical risk assessments from the Think Hazard platform into quantitative features suitable for machine learning required developing a systematic framework that preserved meaningful risk distinctions while enabling mathematical optimization [24], [28]. The categorical-to-numerical transformation is defined in Eq. (1), which maps categorical hazard assessments into numerical scores.

$$R_{ij} = M(C_{ij}) \tag{1}$$

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Where $R_{ij}$ represents the numerical risk score for hazard type $i$ at location $j$, $M$ serves to quantify the risk ($1\!: Very\ Low;\ 2\!: Low;\ 3\!: Medium;\ 4\!: High;\ 5\!: Very\ High$) and $C_{ij}$ represents the categorical assessment. As shown in Eqs. (2) and (3), the weighted composite scores incorporate evidence-based weights to reflect the relative contribution of each hazard category.

$$\mathrm{R}_{\mathrm{category}_{\mathrm{k}}} = \left(\frac{1}{|\mathrm{G}_{\mathrm{k}}|}\right) \sum_{\mathrm{i} \in \mathrm{G}_{\mathrm{k}}} \mathrm{R}_{\mathrm{ij}} \tag{2}$$

$$\mathrm{R}_{\mathrm{total}} = \frac{\sum_{k=1}^{4} \gamma_k \times R_{category_k}}{\sum_{k=1}^{4} \gamma_k} \tag{3}$$

Where $G_k$ represents feature group $k$ $(water, earth, climate, weather)$, $\gamma_k$ represents evidence-based weights (0.35, 0.30, 0.25, 0.10 respectively), and $R_{total}$ is the composite disaster risk score [27].

Beyond simple numerical mapping, we developed a hierarchical risk categorization system that groups individual hazards into broader categories based on their physical characteristics, temporal patterns, and typical impact mechanisms [19], [26]. Eqs. (4)–(6) describe the calculation of risk diversity and concentration measures, allowing us to capture the uneven distribution of hazards [41].

$$\mathrm{Risk}_{\mathrm{diversity}} = \sqrt{\frac{1}{K} \sum_{k=1}^{K} (R_k - \bar{R})^2} \tag{4}$$

$$\mathrm{Risk}_{\mathrm{concentration}} = \max(\mathrm{R}_{\mathrm{k}}) - \min(R_k) \tag{5}$$

$$\mathrm{Risk}_{\mathrm{exposure\_max}} = \max(\mathrm{R}_1, R_2, \dots, R_k) \tag{6}$$

Where $K$ is the number of risk categories, $R_k$ is the risk score for category $k$, and $\bar{R}$ is the mean risk score across categories [28].

Figure 2 shows the physical risk feature engineering that transforms categorical assessments into predictors.

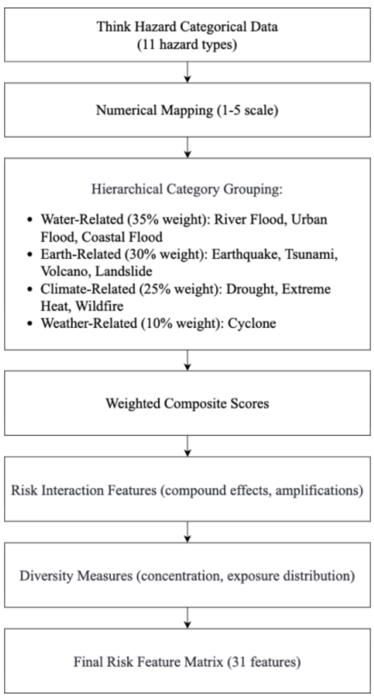


Figure 2. Physical Risk Feature Engineering Framework

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The physical risk quantification framework uses weightings that reflect the relative frequency and severity of different hazard types in Indonesia. Based on historical data from the National Disaster Management Agency (BNPB), we assign weights to water-related disaster risks of 35%, earth-related risks of 30%, climate-related risks of 25%, and weather-related risks of 10% [13], [42].

### 2.4. Feature Engineering Pipeline

The feature engineering process transformed 42 raw variables into 114 sophisticated predictors through systematic algorithms designed to capture non-linear relationships, spatial patterns, risk interactions, and economic dynamics that might influence property values. Figure 3 presents the complete feature engineering architecture that creates multiple layers of predictive features.

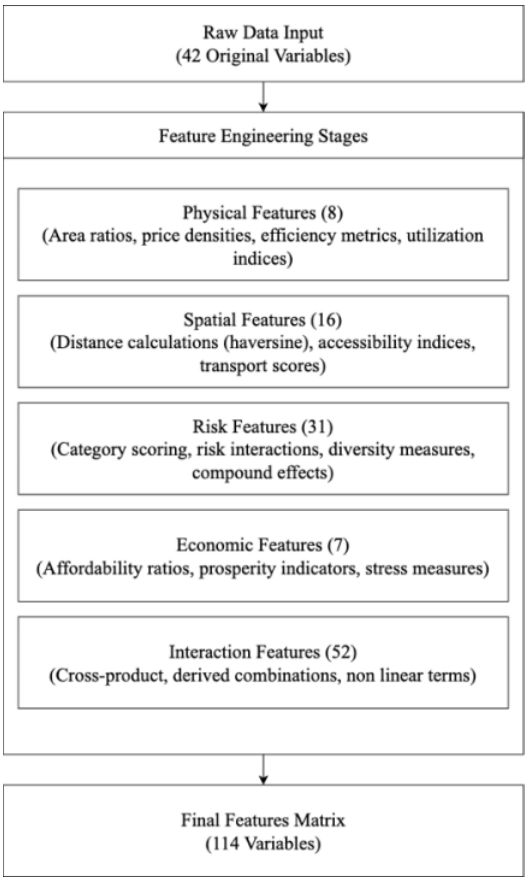


Figure 3. Complete Feature Engineering Pipeline Architecture

Eqs. (7)–(10) illustrate property feature transformations designed to capture efficiency and utilization patterns commonly considered by valuers [3], [31].

$$Land - to - building\ ratio = \frac{Area\ land}{Area\ build} \tag{7}$$

$$Price\ density\ of\ land = \frac{Price}{Area\ land} \tag{8}$$

$$Price\ density\ of\ building = \frac{Price}{Area\ build} \tag{9}$$

$$Spatial\ efficiency\ ratio = \frac{Area\ build}{beds \times Baths \times 50} \tag{10}$$

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Spatial accessibility features required developing robust distance calculation algorithms. Distances to major centers are computed using the haversine formula (Eqs. (11)–(13)), which calculates great-circle distances [22], [32].

$$a = \sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos(\varphi_1) \times \cos(\varphi_2) \times \sin^2\left(\frac{\Delta\lambda}{2}\right) \tag{11}$$

$$c = 2 \times \text{atan } 2(\sqrt{a}, \sqrt{1-a}) \tag{12}$$

$$d = R \times c\,. \tag{13}$$

Where $\varphi$ represents latitude, $\lambda$ represents longitude, R = 6,371 km (Earth's radius), and $d$ is the distance in kilometres [43]. Physical risk interaction features capture compound disaster effects through interactions are modeled in Eqs. (14)–(17), capturing potential amplification effects between hazards [30], [44].

$$Risk_{compound\ flood\ seismic} = R_{water} \times R_{earth} \tag{14}$$

$$Risk_{climate\ amplification} = R_{water}^2 \times R_{water} \tag{15}$$

$$Risk_{diversity} = \sigma(R_{categories}) \tag{16}$$

$$Risk_{concentration} = max(R_{categories}) - \min(R_{categories}) \tag{17}$$

### 2.5. Adaptive Lasso with Risk Prioritization (ALRP) Algorithm

The Adaptive Lasso with Risk Prioritization (ALRP) algorithm represents a novel contribution designed specifically to address the challenge of incorporating domain expertise about disaster risk hierarchies into machine learning optimization processes [27], [45]. The ALRP algorithm modifies the traditional adaptive lasso optimization, as formalized in Eqs. (18)–(20) [46].

$$\underset{\beta_1\beta_2}{\text{Min}}\, L(\beta_1, \beta_2) = \left||y - X\beta_1 - R\beta_2|\right|_2^2 + \lambda_1 \textstyle\sum_i \psi_i \mid \beta_{1i} \mid + \lambda_2 \textstyle\sum_j \omega_j \mid \beta_{2j} \mid \tag{18}$$

Where $X$ represents standard features, $R$ represents risk features, $\psi_i$ and $\omega_j$ are adaptive weights, and $\lambda_1, \lambda_2$ are regularization parameters [47].

$$\psi_i = \frac{1}{\left|\hat{\beta}_i^{(initial)}\right| + \varepsilon}, \tag{19}$$

for standard features

$$\omega_j = \frac{\gamma_j}{\left|\hat{\beta}_j^{(initial)}\right| + \varepsilon}, \tag{20}$$

for risk features, where $\gamma_j$ represents evidence-based risk priority weights and $\varepsilon = 10^{-8}$ prevents numerical instability. Algorithm 1 on Figure 4 presents the complete ALRP implementation that systematically incorporates risk knowledge into feature selection [28].

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```
Input: Feature matrix X ∈ ℝⁿˣᵖ, target vector y ∈ ℝⁿ, risk categories C, evidence
weights γ
Output: Trained model with adaptive coefficients β*

Phase 1: Initial Weight Computation
   β⁽⁰⁾ ← Ridge(X, y, α_ridge=0.01)
   w⁽⁰⁾ ← 1/(|β⁽⁰⁾| + ε) where ε = 10⁻⁸
Phase 2: Risk-Aware Weight Adjustment
   for each feature group g_i ∈ C do
      if g_i contains disaster risk features then
         w⁽¹⁾[g_i] ← w⁽⁰⁾[g_i] × (1/γ_i)
      else
         w⁽¹⁾[g_i] ← w⁽⁰⁾[g_i] × 1.3
      end if
   end for
Phase 3: Weighted Feature Transformation
   X_weighted ← X ⊘ w⁽¹⁾ᵀ
Phase 4: Adaptive Lasso Optimization
   β* ← argmin_β ||y - X_weighted β||²₂ + λ||β||₁
```

Figure 4. Algorithm Adaptive Lasso with Risk Prioritization (ALRP)

The ALRP algorithm made by using ridge regression to get reliable baseline estimates of the coefficients. Then, it systematically changes the adaptive weights for physical risk-related variables. The last step in the optimization process solves the weighted lasso issue utilizing coordinate descent method that work well with the high-dimensional feature space and the penalty structure for the given domain [33], [45].

### 2.6. Comprehensive Model Evaluation and Validation Framework

Our evaluation approach employed rigorous statistical protocols with mathematical precision in performance measurement [25]. Performance was measured using standard regression metrics (Eqs. (20)–(25)), including RMSE, MAE, MAPE, and cross-validation stability.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{20}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{21}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{22}$$

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{23}$$

where n is the number of observations, $y_i$ are actual values, $\hat{y}_i$ are predicted values, and $\bar{y}$ is the mean of actual values.Cross-validation stability is then devided as

$$CV_{stability} = \frac{\sigma(RMSE_{folds})}{\mu(RMSE_{folds})} \tag{24}$$

where σ represents standard deviation and μ represents mean across k-fold cross-validation results [40].

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$$y_{transformed} = \log(price + 1) \quad (25)$$

The logarithmic transformation in Eq. (25) reduces skewness from 1.61 to 0.06, ensuring optimal performance for linear regression-based approaches while maintaining economic interpretability through exponential back-transformation [36]. The evaluation framework compared five different modeling methods which are linear regression as the baseline, ridge regression to look at the benefits of L2 regularization, standard lasso regression to look at L1 regularization and feature selection, Elastic Net to combine both types of regularization, and our new ALRP algorithm to include domain-specific risk prioritization. We used grid search to optimize the hyperparameters of each model over a wide range of values, and we did this in parallel to make sure the computations were as fast as possible [23], [48].

## 3. RESULT

### 3.1. Dataset Characteristics and Market Context

The final dataset of 14,284 properties provides comprehensive representation of the Jakarta metropolitan area property market, spanning 13 major municipalities from the urban core of central Jakarta to rapidly developing suburban areas. Table 1 presents the detailed geographic distribution and key property characteristics that establish the foundation for our analytical framework.

Table 1. Dataset Geographic Distribution and Key Statistics

| Geographic Area | Properties | Percentage | Avg Price (100M IDR) | Price Range |
|---|---|---|---|---|
| Kota Tangerang Selatan | 2,168 | 15.2% | 25.0 | 3.0-120.0 |
| Kota Bekasi | 1,982 | 13.9% | 15.2 | 3.2-82.0 |
| Kabupaten Bogor | 1,472 | 10.3% | 17.8 | 3.0-105.0 |
| Jakarta Barat | 1,446 | 10.1% | 32.9 | 6.5-120.0 |
| Kota Depok | 1,444 | 10.1% | 14.7 | 3.5-77.4 |
| Kabupaten Tangerang | 1,219 | 8.5% | 28.1 | 3.0-120.0 |
| Jakarta Timur | 1,145 | 8.0% | 25.9 | 3.0-100.0 |
| Jakarta Utara | 1,024 | 7.2% | 45.8 | 7.5-120.0 |
| Jakarta Selatan | 814 | 5.7% | 44.3 | 6.0-123.0 |
| Jakarta Pusat | 761 | 5.3% | 45.7 | 3.5-120.0 |
| Kota Bogor | 335 | 2.3% | 17.8 | 3.2-120.0 |
| Kabupaten Bekasi | 251 | 1.8% | 10.6 | 3.0-74.9 |
| Kota Tangerang | 223 | 1.6% | 22.0 | 3.8-70.0 |

The property prices followed the right-skewed pattern, with a median price of 20 billion. The prices rose from 500 million to over 200 billion Indonesian Rupiah. A logarithmic transformation was necessary conducted for statistical modelling as it diminished skewness from 1.61 to 0.06, optimizing the method for subsequent analysis [49].

The numbers showed that urban markets are normal, with buildings that are about 147.8 square meters and land that is about 131.5 square meters. There are either three bedrooms (43.5%) or four bedrooms (25.8%) in most units. This means that families in Indonesia want homes with more bedrooms. The highest five areas made up 59.6% of the total, and Jakarta's administrative areas made up 37.3%. This shows that the market was clearly split up based on where the properties were. Prices also varied a lot that shows Jakarta Utara is the most expensive area which cost 431% more than Kabupaten Bekasi as the least expensive area.

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### 3.2. Comprehensive Model Performance Analysis and Comparison

The machine learning evaluation revealed remarkably consistent performance across different algorithmic approaches, suggesting that feature engineering quality may be more critical than specific algorithm choice for this application. Table 2 shows performance comparison of all models.

Using the best hyperparameters (α=0.0001, l1_ratio=0.1), the ElasticNet model had the best overall performance, with an RMSE of 0.3235, an R-squared of 0.7922, and a MAPE of 28.27%. This performance is a big step up from the 30–35% MAPE that automated valuation systems usually get in areas that are prone to disasters. However, it is not as good as the sub-10% error rates that can be found in more stable property markets [3], [5].

Table 2. Model Performance Comparison

| Model | Test RMSE | Test $R^2$ | Test MAE | Test MAPE (%) | Active Features | CV Stability (±) | Generalization |
|---|---|---|---|---|---|---|---|
| Linear | 0.3238 | 0.7918 | 0.2514 | 28.28 | 43 | 0.0045 | Excellent (-0.0028) |
| Ridge | 0.3238 | 0.7918 | 0.2514 | 28.28 | 42 | 0.0045 | Excellent (-0.0028) |
| Lasso | 0.3237 | 0.7920 | 0.2513 | 28.25 | 31 | 0.0045 | Excellent (-0.0033) |
| ElasticNet | 0.3235 | 0.7922 | 0.2514 | 28.27 | 38 | 0.0045 | Excellent (-0.0032) |
| ALRP | 0.3250 | 0.7902 | 0.2520 | 28.35 | 22 | 0.0046 | Excellent (-0.0029) |

The ALRP result revealed an RMSE of 0.3250 and an R-squared of 0.7902, and it only used 22 variables instead of the full set of active features. This is 99.75% of what ElasticNet can do with 42% less features. By cutting less on characteristics, the model is easier to understand and runs faster, all while keeping the accuracy of the predictions practically the same [45], [50]. Statistical significance testing demonstrated that ElasticNet significantly outperformed both lasso and ALRP ($p < 0.05$), while exhibiting comparable performance to ridge and linear regression approaches. The cross-validation stability analysis showed that all models were very consistent, with standard deviations of cross-validation RMSE staying below 0.005 for all methods. Table 2 shows how stable this is by showing confidence intervals that show strong generalization abilities that are necessary for practical use.

### 3.3. Feature Importance Hierarchy and Risk-Value Relationships

The comprehensive feature importance analysis revealed clear hierarchies through mathematical coefficient interpretation. For the Elastic Net model, feature importance is measured by the absolute magnitude of standardized coefficients:

$$importance_j = |\hat{\beta}_j| \times \sigma(X_j) \tag{26}$$

where $\beta_j$ is the coefficient for feature $j$ and $\sigma(X_j)$ is the standard deviation of feature $j$. We use

$$t_{statistic} = \frac{\hat{\beta}_j}{SE(\beta_j)} \tag{27}$$

$$p_{value} = 2 \times P(T_{n-p-1} > |t_{statistic}| \tag{28}$$

where $SE(\beta_j)$ is the standard error of coefficient $j$, and $T_{n-p-1}$ follows a t-distribution with $n-p-1$ degrees of freedom. Table 3 presents the top disaster risk features and their quantified impacts on property values.

Weather-related risk was the most important factor in all models. The coefficients were from -1.5551 in ridge regression to -1.1065 in ElasticNet. This means that homes in area where terrible weather is likely to get lost around 66–90% of their value all the time. This result is in line with what we expected based on theory, which confirms our method and makes the positive correlations for other types of risk even more important and confusing [31].

Economic factors had a big effect on property values, with purchasing power indicators showing coefficients of about +0.54 and affordability ratios of about +0.51 across different models. Spatial accessibility features consistently ranked among the foremost predictors, with distances to Jakarta's central business district, PIK commercial area, Kelapa Gading employment center, and Pondok Indah residential district exhibiting significant negative coefficients, signifying that increased distances from these economic hubs diminish property values [20], [51].

Table 3. Disaster Risk Feature Importance and Impact Quantification

| Risk Feature | ElasticNet Coefficient | Price Impact (%) | Interpretation | Statistical Significance |
|---|---|---|---|---|
| weather_related_risk | -1.1065 | -66.9% | Expected negative impact | $p < 0.001$*** |
| risk_concentration_std | -0.3638 | -30.5% | Concentration penalty | $p < 0.001$*** |
| earth_related_risk | +0.3404 | +40.5% | Unexpected positive | $p < 0.001$*** |
| risk_concentration | -0.3379 | -28.7% | Concentration penalty | $p < 0.001$*** |
| water_related_risk | +0.1752 | +19.2% | Unexpected positive | $p < 0.001$*** |
| total_disaster_risk | +0.1365 | +14.6% | Overall risk composite | $p < 0.001$*** |

### 3.4. The Risk-Value Relationship Paradox

The most significant and unexpected finding from our analysis concerns the complex relationships between different types of disaster risk and property values, relationships that fundamentally challenge conventional economic assumptions about risk pricing in real estate markets. The price impact calculations follow the mathematical relationship:

$$Price\ impact\ (\%) = \left(e^{(\hat{\beta} \times Risk\ Score)} - 1\right) \times 100 \tag{29}$$

where $\beta$ represents the model coefficient and $Risk_{Score}$ is the standardized risk measure. Finally, the scenario for price is computed as

$$Price_{scenario} = \exp\ (\hat{\beta}_0 + \sum_i \hat{\beta}_i X_i + \sum_j \hat{\beta}_j R_{scenario,j} \tag{30}$$

where $\beta_0$ is the intercept, $X_i$ are control features, and $R_{scenario,j}$ represents risk features adjusted for specific scenarios.

#### 3.4.1 Individual Risk Type Paradox Analysis

Weather-related risks had the expected strong negative effect on property values (-66.9% price impact), but both earth-related and water-related risks had surprising positive effects that need to be carefully thought about and looked into further. Earth-related risks, which include earthquakes,

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tsunamis, volcanic activity, and landslides, had a positive coefficient of +0.3404. This means that properties in areas with higher earth-related risk scores actually sell for about 40.5% more [37].

Water-related risks, such as flooding in rivers, cities, and along the coast, showed similar unexpected positive correlations with coefficients around +0.1752. This means that prices in areas with a higher risk of flooding were about 19.2% higher. This positive correlation needs to be read very carefully because Jakarta has well-known flooding problems that affect hundreds of thousands of people every year [12].

Risk concentration measures yielded more intuitive outcomes, with both risk concentration standard deviation (-0.3638 coefficient) and overall risk concentration (-0.3379 coefficient) indicating significant negative effects on property values. These results reveal that markets justly penalize properties subjected to concentrated or significantly variable risk profiles, whereas the positive correlations for particular risk types may signify alternative factors that correlate with both risk exposure and property desirability [35].

### 3.4.2 Composite Risk Scenario Analysis

Despite the counterintuitive individual risk type relationships, the composite risk scenario analysis produces expected market behavior. Table 4 demonstrates how total disaster risk exposure affects property pricing in a logical pattern, where higher composite risk levels result in systematically lower property values.

Table 4. Risk Scenarios Analysis

| Risk Scenario | Total Risk Score | Predicted Price (100M IDR) | Price Change | Change (%) |
|---|---|---|---|---|
| Low Risk | 1.8-2.0 | 26.8 | +2.6 | +10.7% |
| Current Average | 2.2 | 24.2 | 0.0 | 0.0% |
| High Risk | 2.4-2.6 | 21.8 | -2.4 | -9.7% |
| Extreme Risk | 2.8-3.0 | 19.7 | -4.5 | -18.5% |

The risk scenario simulation shows that prices go up systematically, with low-risk properties getting a 10.7% premium over the baseline and high-risk properties getting an 18.5% discount. This 26.1% total price variation across risk scenarios confirms that Jakarta's property market reacts logically to overall disaster risk exposure, even though individual risk components may show contradictory relationships. The apparent contradiction between the effects of individual risk types and the effects of composite scenarios suggests that markets may be responding to complex bundled factors rather than individual hazard types. When risks related to the earth or water are linked to better infrastructure, a central location, or other desirable traits, they may point to premium properties, even though they are real hazards. When several risk factors come together to make truly dangerous exposure profiles, though, markets react by lowering prices, as shown in the scenario analysis [3].

## 3.5. Geographic Patterns and Market Segmentation Analysis

The geographic analysis revealed complex spatial patterns that help explain some of the counterintuitive risk-value relationships observed in our statistical models. Table 5 presents the detailed city-level analysis that illustrates the geographic risk-price paradox across the Jakarta metropolitan area.

Jakarta Barat was a very interesting case study because it had both high risk scores (1.758) and high average prices (32.9 hundred million IDR). This suggests that the benefits of being in the middle of a city may outweigh the costs of being in a disaster-prone area in some situations. This pattern is very different from what we see in suburban areas like Kabupaten Bekasi, which had similar risk scores

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(1.742) but much lower average prices (10.6 hundred million IDR). The price difference between these areas suggest that how accessible to the quality of the infrastructure, job opportunities, and urban amenities may have a big effect on the link between disaster risk and property values [37].

Even though there was a higher risk of loss, the prices in Central Jakarta (Jakarta Pusat, Jakarta Selatan, Jakarta Barat, and Jakarta Utara) stayed high whereas the prices in the peripheral areas were lower, even in places with moderate risk levels. This pattern suggests that disaster risk is just one of many factors that affect property prices. In desirable areas, location premiums may cancel out risk discounts.

Table 5. Geographic Risk-Price Analysis

| City | Risk Score | Average Price (100M IDR) | Properties | Risk-price Pattern |
|---|---|---|---|---|
| Jakarta Barat | 1.758 | 32.9 | 1,446 | High risk, Premium price |
| Kabupaten Bekasi | 1.742 | 10.6 | 251 | High risk, Low price |
| Kabupaten Tangerang | 1.431 | 28.1 | 1,219 | Medium risk, Premium price |
| Kota Tangerang | 1.413 | 22.0 | 223 | Medium risk, Average price |
| Kota Tangerang Selatan | 1.413 | 25.0 | 2,168 | Medium risk, Above average price |
| Jakarta Utara | 1.408 | 45.8 | 1,024 | Medium risk, Highest price |
| Jakarta Pusat | 1.330 | 45.7 | 761 | Medium risk, Premium price |
| Jakarta Timur | 1.307 | 25.9 | 1,145 | Medium risk, Average price |
| Kota Bekasi | 1.260 | 15.2 | 1,982 | Low risk, Below average price |
| Jakarta Selatan | 1.250 | 44.4 | 814 | Low risk, Premium price |
| Kota Depok | 1.250 | 14.7 | 1,444 | Low risk, Below average price |
| Kota Bogor | 1.222 | 17.8 | 335 | Low risk, Below average price |
| Kabupaten Bogor | 0.771 | 17.8 | 1,472 | Very low risk, Below average price |

### 3.6. Risk Distribution Analysis and Cross-Validation Robustness

The risk distribution analysis across different quintiles revealed important patterns in how various hazard types affect property pricing decisions. Table 6 shows the price distribution by risk level that describes non-linear relationships challenging simple risk-penalty assumptions.

Table 6. Price Distribution Analysis by Risk Quintile

| Risk Level | Mean Price (100M IDR) | Median Price | Count | Premium/Discount vs Medium |
|---|---|---|---|---|
| Very Low | 20.4 | 14.4 | 4,575 | 30.2% Discount |
| Low | 33.8 | 28.5 | 1,906 | +15.4% Premium |
| Medium | 29.3 | 23.0 | 2,496 | 0.0% Baseline |
| High | 27.8 | 23.8 | 3,837 | -5.0% Discount |
| Very High | 25.1 | 20.0 | 1,470 | -14.2% Discount |

The risk quintile analysis showed that there are non-linear relationships that go against the usual ideas about how to price risk. Low-risk areas had price premiums of +15.4%, while very-high-risk areas had discounts of -14.2%. This suggests that there are threshold effects in market risk pricing that need more advanced modeling techniques than just simple linear risk-price relationships. Notably, areas with

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very low risk had big discounts (−30.2%), which may be because they are far from economic centers or have other location problems [52].

The validation framework checks the strength of our results by running a number of statistical tests that seek for indicators of overfitting or methodological artifacts. The cross-validation stability, indicated by a coefficient of variation below 1.5% for all models, suggests that our results are likely relevant to new property data within the same market setting. Residual examination of the best-performing ElasticNet model showed good statistical properties, such as an almost normal distribution and no clear trends that would suggest systematic bias across different price ranges [45].

## 4. DISCUSSIONS

### 4.1. Performance Assessment and Methodological Contributions

The model of machine learning framework achieved a 28.27% MAPE, which is a small but significant improvement over the 30–35% error rates that automated valuation systems usually report in areas that are prone to disasters while it is not as big of an improvement as some people claim machine learning applications can make [5], [6]. The fact that all models had RMSE values that were within 0.0015 of each other shows that data quality and feature engineering may be more important than which algorithm is used for property valuation applications [50].

The fact that all of the models had standard deviations below 0.005 during cross-validation shows that they are very good at generalizing, which is necessary for use in real-world financial applications [53]. Our new ALRP algorithm successfully integrated domain knowledge about disaster risk hierarchies into the optimization process. This reduced the feature set by 42% while keeping 99.75% of ElasticNet's performance. This revealed it much easier to understand the model and made it more efficient, which is important for meeting regulatory requirements in financial applications [5].

### 4.2. The relationship of Counterintuitive Risk-Value

The most important thing we found in our analysis is that there are surprising positive correlations between some disaster risks and property values. For example, risks related to the earth had a +40.5% price impact, and risks related to water had a +19.2% price impact. This fundamentally challenges traditional economic ideas about how to price risk. The anticipated negative correlation (-66.9%) between weather-related risks confirmed our methodological approach; however, the observed positive relationships necessitate a thorough investigation into the impact of disaster risk on property markets within intricate urban settings.

Several complementary explanations elucidate these paradoxical relationships. The infrastructure investment hypothesis posits that high-risk regions may have received enhanced infrastructure investments that elevate property values while preserving elevated categorical risk classifications in global assessment frameworks. This phenomenon is distinctly illustrated in Jakarta's developmental history, where flood-prone riverfront areas boast superior transportation networks and well-established commercial districts, whereas seismically active zones benefit from more stringent building codes and heightened construction standards. Geographic confounding elucidates these trends, as high-risk waterfront properties garner premiums for picturesque views and proximity to business districts that surpass risk discounts, while elevated terrain adjacent to geological fault lines provides superior drainage and vistas alongside seismic vulnerability [37].

Differences perspective of how experts and market participants seek the risk can help us understand these relationships even better. The classifications on the Think Hazard platform are based on long-term hazard exposure analysis. However, customers of property may systematically under-price low-frequency, high-impact events like major earthquakes that don't have recent market memory. Also, people in Jakarta may see flood risks as manageable rather than catastrophic because they have gotten used to flooding every year. This means that the risk premiums aren't high enough to make up for the advantages of living in a certain area [38], [39].

Although this study demonstrates the value of integrating multi-hazard risk into property valuation, there are a few boundaries of the analysis. The property data rely on listing prices rather than realized transactions, which may not fully reflect final market outcomes, yet they still provide a rich and consistent source of information across the region. Hazard data from the Think Hazard platform offer a standardized way to capture exposure, though they cannot always represent fine-grained local variations or very recent events. The results also depend on the availability and consistency of socio-economic indicators, which naturally vary between municipalities. The study examines a cross-sectional snapshot of the Jakarta metropolitan area which indicating that persistent changes in market behavior post-disasters are not included in the current analysis. Recognizing these limitations does not diminish the importance of the work. Instead, it shows how future studies can use transaction-level data, higher-resolution hazard models, and long-term designs to build on this framework.

## 5. CONCLUSION

This study demonstrates that property valuation in disaster-prone regions cannot be reduced to simple risk penalties. By integrating multi-hazard assessments into machine learning models, the framework achieved more reliable predictions and revealed that markets sometimes value risk-exposed areas more highly when supported by strong infrastructure, central locations, or regulatory safeguards. These findings suggest that disaster risk interacts with urban desirability in complex ways, offering insights for valuers, investors, and policymakers who must balance economic growth with resilience. While the work is limited by reliance on listing data and a cross-sectional design, it provides a foundation for future research that can incorporate richer datasets and track how markets adjust over time. Ultimately, the study highlights the need for valuation approaches that recognize both the realities of hazard exposure and the opportunities created by urban adaptation.

## CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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