# Spatial dynamics of built-up land development prediction based on cellular automata markov chain in tsunami prone areas of Ternate Island, Indonesia

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**Abstract.** Ternate Island's coastal geography makes it highly susceptible to tsunamis, and increasing built-up land intensifies this risk. This study analyzes the spatial dynamics of built-up land development in tsunami-prone areas using land cover data from 2005, 2015, and 2025, along with driving factors such as elevation, distance from roads, and economic centers. The Cellular Automata-Markov Chain (CA-Markov) method was used to project land cover for 2035 and 2045. Tsunami hazard zones were modeled using elevation, slope, 2025 land cover, and distances from the coastline and rivers. Overlay analysis of built-up land predictions with tsunami hazard zones reveals a continual expansion of built-up areas over time. Tsunami-prone zones were classified into low (31.77%), medium (24.83%), and high (43.40%) hazard levels. The findings show a direct correlation between the expansion of built-up land and increased exposure to tsunami hazards, emphasizing the need for spatial planning strategies to mitigate future risks.

## 1 Introduction

Developing built-up land in tsunami-prone areas like Ternate Island poses an important issue for spatial planning and disaster mitigation in Indonesia's coastal areas [1]. Rapid population growth and urbanization have encouraged the conversion of natural land into residential areas and infrastructure, thereby increasing vulnerability to tsunami disasters and reducing environmental carrying capacity [2]. To understand the dynamics of built-up land change, a spatially-based predictive approach is needed that is able to project future land development patterns by considering disaster risk factors [3].

The Cellular Automata-Markov Chain (CA-Markov) model has proven effective in predicting land cover change and built-up area growth patterns in various regions, including

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in disaster-prone areas [4]. This model combines the statistical prediction capabilities of Markov chains with the spatial analysis power of cellular automata [5], resulting in realistic and accurate simulations of land change over the long term. The use of multi-temporal satellite image data, such as Landsat 5 for 2005 and Landsat 8 OLI TIRS for 2015 and 2025, is essential in supporting detailed and periodic land change analysis.

Ternate Island, as a small island with a high level of vulnerability to tsunamis, requires data-based spatial management strategies and precise spatial projections to reduce disaster risk [6]. By utilizing multi-temporal Landsat image data, this research is able to map the change of built-up land from 2005 to 2015 to 2025 and predict the development of built-up land in 2035 and 2045 using the CA-Markov model. The results of these predictions are crucial for determining safe zones, mitigation priorities, and adaptive spatial planning in tsunami-prone areas.

Factors such as population growth, accessibility, and space requirements are the main drivers of built-up land change in urban and coastal areas [6]. Integration of remote sensing data from Landsat imagery with the CA-Markov model can improve prediction accuracy and support evidence-based decision-making for disaster risk management in Ternate. Remote sensing technology and geographic information systems (GIS) are essential for regular monitoring of land change and evaluation of the effectiveness of spatial planning policies [8,9].

Based on the explanation of the situation on Ternate Island, the research question is: how will the spatial dynamics of built-up land development in tsunami-prone areas change in 2005, 2015, 2025, 2035, and 2045 using cellular automata markov chain. The hypothesis derived from the above problem is that built-up land development in the coastal areas of Ternate Island will continue to increase in line with population growth over time. The area of built-up land in tsunami-prone areas shows a direct relationship to the development period. Therefore, with each passing year, the area of residential land in the area will increase. The research object is Ternate Island, specifically the tsunami-prone areas, but with increasing development there.

## 2 Methodology

This study was conducted on Ternate Island, North Maluku Province, Indonesia (Figure 1) The research object is Ternate Island, specifically the tsunami-prone areas, but with increasing development there (the coastal areas of the island)\. The variables of this study consisted of built-up land development and tsunami-prone areas. This study used Landsat 5 TM image data from 2005 and Landsat 8 OLI/TIRS data from 2015 and 2025, which were downloaded from the official website of the United States Geological Survey, https://earthexplorer.usgs.gov. Landsat 5 TM image data recorded on 10.04.2005 and Landsat 8 OLI/TIRS recordings from 14.04.2015 and 25.04.2025 were used to analyze the development of built-up land in those years. To predict the future development of built-up land on Ternate Island (2035 & 2045), the driving factors are elevation obtained from elevation model data, distance from roads, and distance from public facilities obtained from the Indonesian Geospatial Information Agency. For the analysis of tsunami-prone areas using land elevation data, slope was obtained from digital elevation model data analysis, and distance from the coastline and river was obtained from the results of buffer analysis using ArcGIS Pro software.

The processing of tsunami hazard and settlement exposure variables used data on distance from coastline, distance from river, land elevation, and slope modified from previous researchers [9] (Table 1). These parameters were analyzed using the weighted overlay method with the equation: Tsunami Hazard = [(Elevation score ∗ 30) + (Slope score ∗ 25) + (Distance from coastline score ∗ 30) + (Distance from river score ∗ 15)]. The results of the overlay of tsunami hazard variables were then classified into 3 hazard classes: low, medium, and high. The variable weights in tsunami risk assessments differ because elevation and distance from the coastline are considered the most influential (weighted at 30) because they determine direct exposure to tsunami waves. Slope (weighted at 25) influences the distribution of inland water, while distance from rivers (weighted at 15) plays a lesser role as a flood ingress route. These weightings are based on a Multicriteria Decision Analysis method such as AHP, which combines expert opinion and statistical analysis to reflect the relative influence of each parameter. The greater the influence of the causal factor, the higher the weighting value assigned [10, 11].

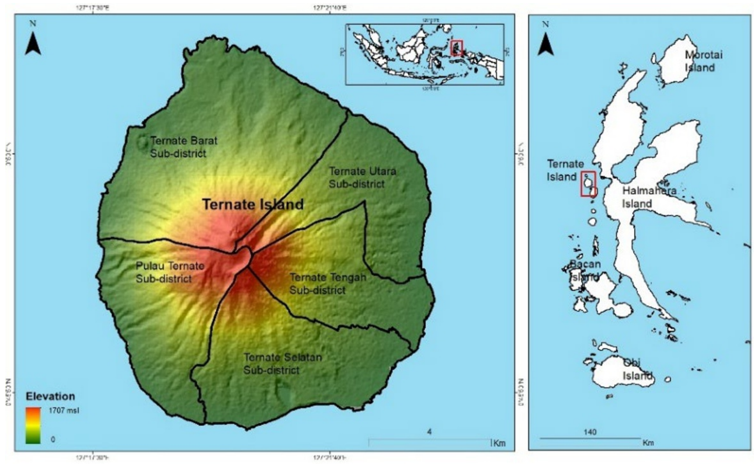


**Fig. 1.** Research location: Ternate Island, Maluku Utara Province, Indonesia.

**Table 1.** Classification of tsunami hazard parameters.

| Variables | Classification | Score | Weight |
|---|---|---|---|
| Elevation | <10 masl | 5 | 30 |
| | 11-25 masl | 4 | |
| | 51-100 masl | 3 | |
| | 101-150 masl | 2 | |
| | >150 masl | 1 | |
| Slope | <2 % | 5 | 25 |
| | 3-5% | 4 | |
| | 6-15% | 3 | |
| | 16-40% | 2 | |
| | >40% | 1 | |
| Distance from coastline | <500 m | 5 | 30 |
| | 501-1000 m | 4 | |
| | 1001-1500 m | 3 | |
| | 1501-1300 m | 2 | |
| | >1300 m | 1 | |
| Distance from river | <100 m | 5 | 15 |
| | 101-200 m | 4 | |
| | 201-300 m | 3 | |
| | 301-500 m | 2 | |
| | >500 m | 1 | |

Source: [9], [11]

The prediction map of built-up land development of Ternate Island in 2025, 2035, and 2045 was then overlaid with the tsunami hazard map to obtain the prediction map of built-up land affected by tsunami hazard in Ternate Island.

## 3 Results and discussion

### 3.1 Development of built-up land on Ternate Island in 2005, 2015, and 2025

The development of built-up land in Ternate Island shows a significant increasing trend from 2005 to the 2025 projection (Fig.2). In 2005, the built-up land area was recorded at 1,551.41 hectares, or 15.19% of the total area, then increased to 1,867.06 hectares (18.28%) in 2015, and is estimated to reach 2,131.15 hectares (20.87%) in 2025. This increase indicates the expansion of settlement areas and development activities that continue to grow in line with population growth and space needs on Ternate Island. Meanwhile, undeveloped land decreased from 8,593.36 hectares (84.14%) in 2005 to 8,013.02 hectares (78.47%) in 2025, indicating the conversion of open land to built-up land (Fig.3).

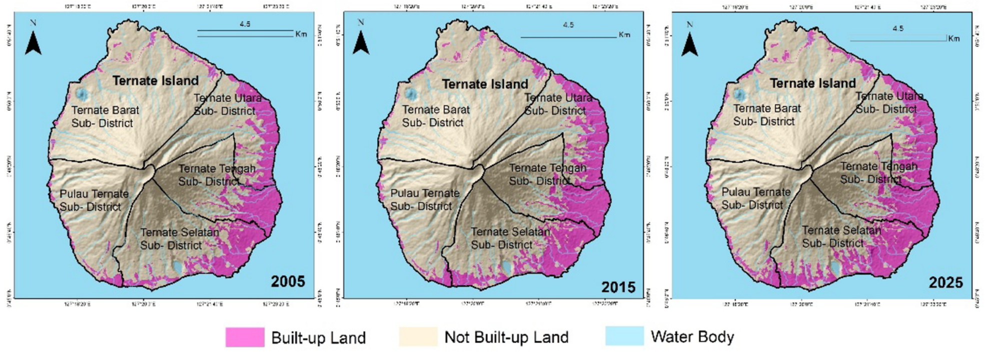


**Fig. 2.** Land cover map of Ternate Island in 2005, 2015, 2025.

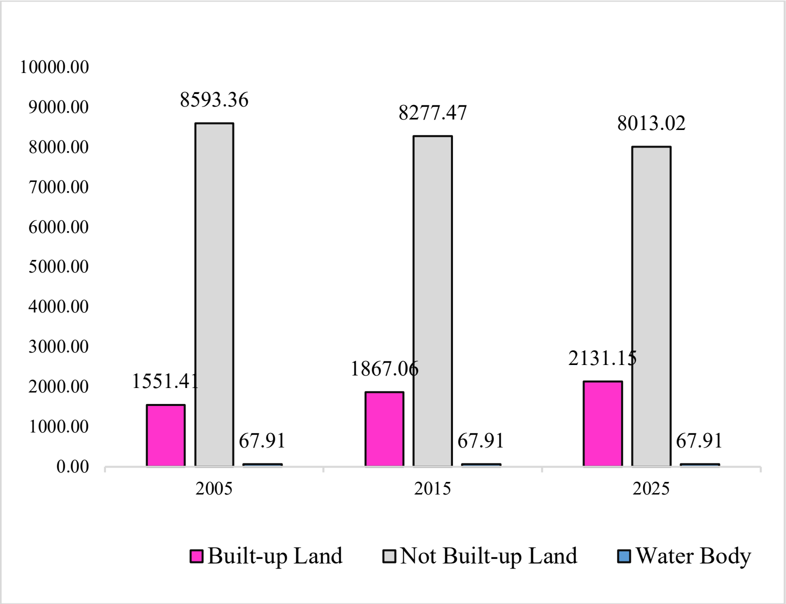


**Fig. 3.** Land cover area of Ternate Island in 2005, 2015, 2025.

These land cover changes are particularly relevant in the context of tsunami-prone areas such as Ternate Island, as an increase in built-up land in coastal and low-lying areas can increase the risk of community vulnerability to tsunami disasters. The Cellular Automata-

Markov Chain model used in this study is effective in predicting the spatial dynamics of built-up land change, which can be an important tool in spatial planning and disaster risk mitigation in the future. Thus, the results of this analysis can serve as a basis for policymakers in regulating regional development to make it more sustainable and safe from tsunami threats.

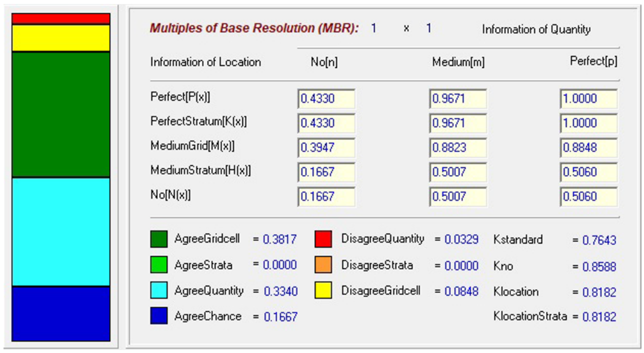


**Fig. 4.** Model prediction validation results with kappa test.

### 3.2 Prediction of built-up land on Ternate Island in 2035 and 2045

Before predicting the rate of development of built-up land in 2035 and 2045, an initial simulation process was carried out for 2025 using the driving factors that have been prepared, including the results of overlaying elevation variables and distance from roads and public facilities. After making the 2025 model, the model must be tested for accuracy. An accuracy test is conducted to determine whether the first generated model can be applied to produce the second prediction model. The accuracy test was conducted with existing land cover data in 2025 as reference data and 2025 land cover prediction model data as a comparison image. If the kappa value accuracy test results are more than 70%, then the model is declared suitable for use [12]. The results of the accuracy test can be obtained kappa value (standard K) of 0.76, or 76.43% (Fig.4), which indicates that this accuracy value is very good and can be applied to model the land cover of Ternate Island in 2035 and 2045.

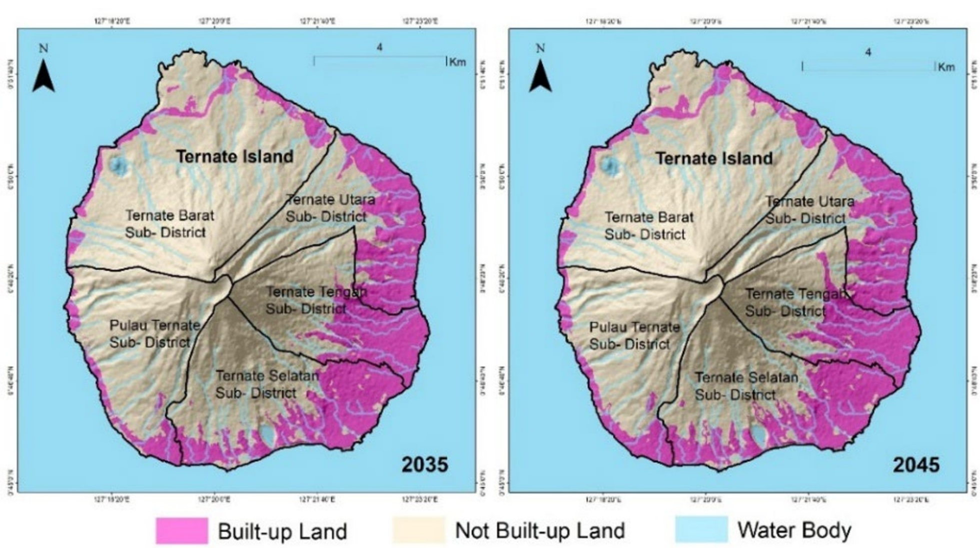


**Fig. 5.** Predicted land cover map of Ternate Island in 2035, 2045.

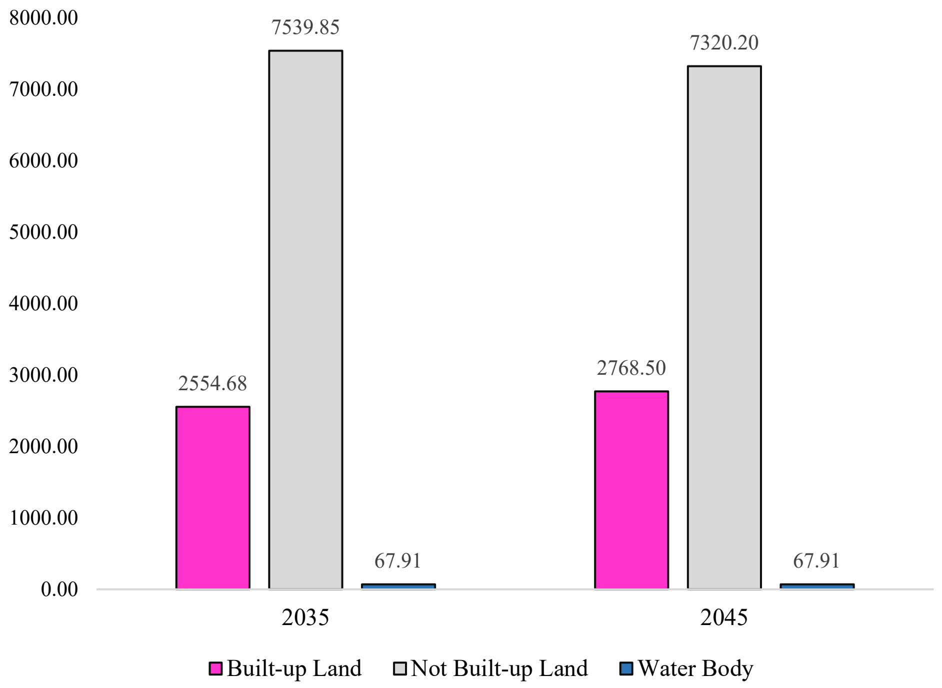


**Fig. 6**. Predicted land cover area of Ternate Island in 2035, 2045.

Land cover prediction of Ternate Island using the Cellular Automata-Markov Chain model shows that in 2035, the area of built-up land is estimated to reach 2,554.68 ha, or about 25.14% of the total area, while non-built-up land is 7,539.85 ha, or 74.19%, and water bodies remain stable at 67.91 ha, or 0.67% (Fig 5,6). This increase in built-up land is in line with urbanization trends in coastal areas and small islands, where development pressures tend to increase in disaster-prone areas, including tsunami-prone zones [13]. Previous studies have shown that CA-Markov models are effective in projecting the spatial dynamics of land change, especially in areas with high development pressure and significant disaster risk [14].

In 2045, projections show that built-up land increases to 2,768.50 ha, or 27.26%, while non-built-up land decreases to 7,320.20 ha (72.07%), and water bodies remain relatively constant. This trend of built-up land growth indicates the expansion of residential areas and infrastructure that can increase exposure to tsunami risk, especially if development occurs in coastal areas [15]. Studies in Banda Aceh and other coastal areas prove that the growth of built-up land in tsunami-prone zones requires special attention in spatial planning and spatial prediction-based disaster mitigation so that sustainable development is maintained and disaster risks are minimized [2].

### 3.3 Tsunami-prone areas of Ternate Island

Spatial analysis of tsunami vulnerability in Ternate Island shows that low-vulnerability areas cover an area of 4,410.25 ha, or about 43.40% of the total island area (Figure 7). The medium vulnerability zone covers 2,523.43 ha, or 24.83%, while the high vulnerability zone covers 3,228.08 ha, or 31.77%, which is generally located in coastal and lowland areas. This spatial distribution is in line with the results of previous studies, which confirmed that topography, distance from the coastline, and land elevation are the main factors influencing the level of tsunami vulnerability in volcanic islands such as Ternate [16].

The high proportion of areas with moderate to high vulnerability emphasizes the importance of integrating tsunami risk maps in regional spatial planning, particularly for controlling built-up land development in vulnerable zones. Recent studies emphasize that the development of settlements and infrastructure in tsunami-prone areas without considering risk mitigation can increase the potential for socio-economic losses and casualties in the event of a disaster [1]. Therefore, the results of this analysis are very important as a basis for decision-making in coastal area management and strengthening spatially based mitigation strategies in Ternate Island.

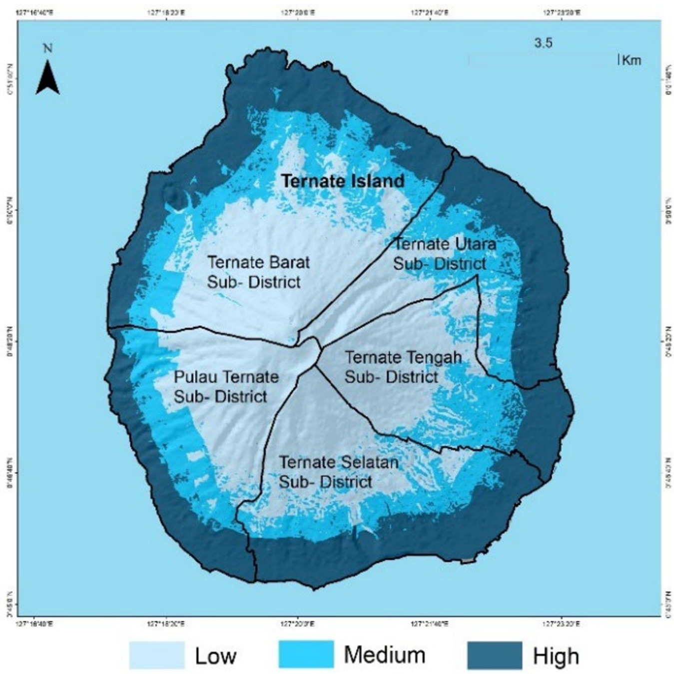


**Fig. 7.** Tsunami prone areas of Ternate Island.

### 3.4 Predicted development of built-up land in 2025, 2035, and 2045 in tsunami-prone areas

Predictions of the development of built-up land in tsunami-prone areas of Ternate Island in 2025 show that most of the built-up land is located in the high-risk zone, covering 1,598.44 ha, or 75.38% of the total built-up land in tsunami-prone areas. Meanwhile, built-up land in the medium-risk zone reaches 466.71 ha (22.01%), and in the low-risk zone only 55.31 ha (2.61%), indicating a tendency for development that is still concentrated in coastal and lowland areas that are highly vulnerable to tsunami threats (Fig.8, 9). This phenomenon is in line with the findings of Amri et al., who stated that the growth of built-up land in high-risk zones is often driven by land limitations and high economic activity in coastal areas [2].

In 2035, predictions show an increase in built-up land in all risk zones, with the high-risk zone still dominating at 1,858.14 ha, or 72.75% of the total built-up land in tsunami-prone areas. The medium-risk zone increased to 560.00 ha (21.92%), and the low-risk zone increased to 136.17 ha (5.33%), indicating a shift in development towards relatively safer zones, although still dominated by high-risk areas. The study by Latue & Rakuasa, emphasizes that without strict spatial policy intervention, the trend of development in high-risk zones will continue and increase the potential for losses during disasters [9].

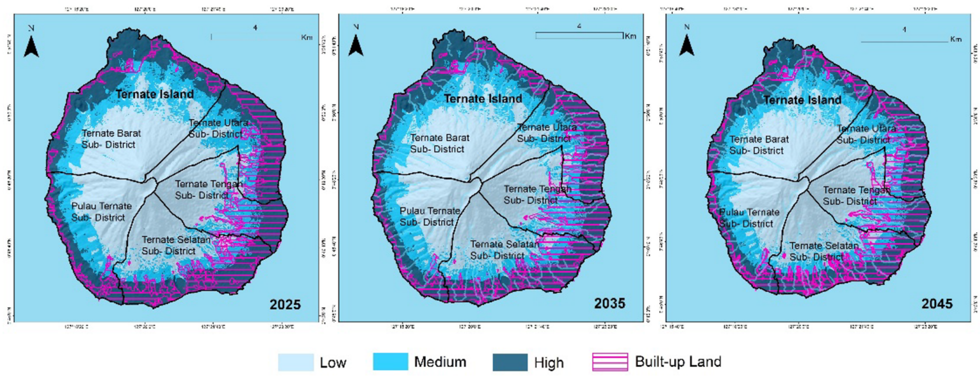


**Fig. 8.** Predicted development of built-up land 2025, 2035, 2045 in tsunami prone areas.

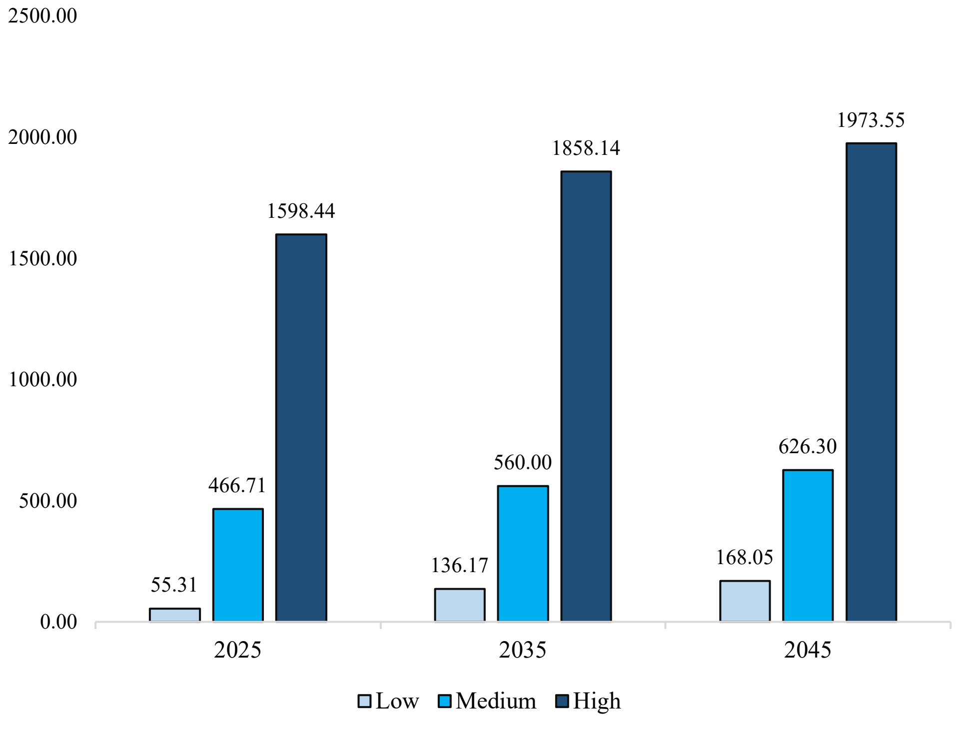


**Fig. 9.** Predicted area of built-up land development 2025, 2035, 2045 in tsunami prone area.

By 2045, built- up land in the high-risk zone is projected to reach 1,973.55 ha, or 71.30%, while the medium-risk zone rises to 626.30 ha (22.63%) and the low-risk zone to 168.05 ha (6.07%). This pattern shows that despite a slight increase in development in low- and medium-risk zones, the majority of development still occurs in areas with high tsunami risk, which can increase the socio-economic vulnerability of coastal communitie. Therefore, the prediction results confirm the importance of integrating spatial modeling results into disaster mitigation policies and risk-based spatial planning to reduce the negative impacts of future tsunamis. This result is in line with research conducted by Latue and Rakuasa on the Spatial Dynamics of Tsunami-Prone Areas in Nusaniwe District, Ambon City, Maluku Province, which obtained the results of an analysis of the tsunami hazard map in Nusaniwe District which showed an increase in the area of built-up land in tsunami-prone areas in 2022 and 2031, which was caused by the built-up/residential land area continuing to increase along with population growth and the increasing need for land for building [9].

## 4 Conclusion

Predictions of built-up land development on Ternate Island using the Cellular Automata-Markov Chain model, the object of the study, show a significant upward trend, particularly in tsunami-prone zones, with development dominating in high-risk areas (71.30% in 2045) compared to low-risk zones (6.07%). This indicates that urbanization and development pressures remain concentrated in vulnerable coastal areas, increasing community exposure to tsunami threats without adequate mitigation strategies. These findings emphasize the urgency of integrating risk-based spatial planning policies, strengthening zoning of disaster-prone areas, and implementing sustainable development to reduce future socio-economic vulnerability. This study also suggests the need for a transdisciplinary approach in engaging stakeholders to address risk perception bias and ensure adaptive multi-hazard development on small islands like Ternate.

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