



Spatial Vulnerability Analysis of Tidal Flooding in Kandanghaur, Indramayu

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<https://doi.org/10.18280/ijstdp.210817>

ABSTRACT

Received: 2 July 2026

Revised: 12 August 2026

Accepted: 19 August 2026

Available online: 31 August 2026

Keywords:

coastal vulnerability, disaster risk, geographic information system, Indramayu, tidal flooding

Recurring tidal flooding threatens low-lying coastal settlements in Kandanghaur, Indramayu, but village-level vulnerability evidence has been difficult to trace across social, economic, physical, and environmental dimensions. This study applies the Indonesian National Disaster Management Agency (BNPB) disaster-risk framework to Eretan Wetan, Eretan Kulon, and Kertawinangun using field observations, demographic and economic records, OpenStreetMap building footprints, manually interpreted land use, and a secondary tidal-flood hazard layer. Geographic information system (GIS) overlay, scoring, and weighted aggregation were used to derive component and composite indices. Recalculation from the village-level indicators yields high composite vulnerability in all villages: Eretan Kulon 0.89, Eretan Wetan 0.88, and Kertawinangun 0.74. Economic vulnerability is high throughout, physical vulnerability is high in all villages, social vulnerability is high in the two Eretan villages and medium in Kertawinangun, and environmental vulnerability is medium. The transparent component tables revise total physical and economic exposure to approximately IDR 300.2 billion. A $\pm 10\%$ weight sensitivity test preserves the village ranking, while a $\pm 20\%$ housing-cost test produces a total exposure range of approximately IDR 275.2-325.2 billion. The findings support targeted coastal adaptation and more auditable vulnerability mapping.

1. INTRODUCTION

Tidal flooding (rob) is a recurrent coastal hazard along the northern coast of Java, where low relief, sea-level rise, tidal variability, shoreline change, and land subsidence can combine to generate repeated inundation and cumulative damage [1-9]. Unlike short-duration flooding, recurrent tidal inundation progressively disrupts housing, public services, productive land, and ecosystem functions. Village-scale vulnerability analysis is therefore important because similar hazard footprints can produce different consequences depending on demographic structure, built assets, livelihood dependence, and ecological conditions [10-14].

Kandanghaur Subdistrict in Indramayu Regency is a relevant case because Eretan Wetan, Eretan Kulon, and Kertawinangun are directly exposed to the Java Sea and contain dense settlements, rice fields, and aquaculture ponds. Previous Indonesian studies demonstrate the usefulness of geographic information system (GIS) for coastal flood and building vulnerability assessment [1, 3, 15-24]. However, the traceability of composite vulnerability indices remains a methodological concern when component scores, weights, and monetary assumptions are not reported at comparable levels of detail.

The study evaluates social, economic, physical, and environmental vulnerability using the Indonesian National Disaster Management Agency (BNPB) framework. The analysis has three objectives: (1) to report village-level

indicators and calculations symmetrically across all four dimensions; (2) to clarify the status and limitations of the hazard, OpenStreetMap (OSM), and Google Earth inputs; and (3) to test the robustness of composite rankings and monetary exposure to plausible changes in weights and housing-loss assumptions. This structure separates methodological assumptions from interpretation so that each vulnerability component and the resulting composite index can be independently audited.

1.1 Conceptual framework of multidimensional vulnerability

Disaster vulnerability is multidimensional because the consequences of a hazard depend not only on the intensity of the physical event but also on the people, assets, livelihoods, and ecosystems located within the exposed area. Social vulnerability reflects demographic and socioeconomic conditions that can constrain preparedness, evacuation, coping, and recovery. Physical vulnerability represents the susceptibility and value of buildings and infrastructure. Economic vulnerability captures the exposure of productive land and income-generating sectors, whereas environmental vulnerability represents natural assets that may be damaged while also contributing to coastal protection. Treating these dimensions separately before aggregation avoids interpreting a single composite score as if all villages were vulnerable for the same reasons [10-12, 25-30].

This distinction is particularly relevant to recurrent tidal flooding. Repeated inundation can degrade housing and public facilities, interrupt mobility and services, reduce agricultural and aquaculture productivity, and alter coastal ecosystems even when an individual event is not catastrophic. Consequently, vulnerability assessment must capture both direct asset exposure and the social and ecological conditions that influence longer-term recovery. The BNPB framework provides a policy-oriented basis for this multidimensional interpretation and allows the component indicators to be compared using a common scoring scale. Related studies have also examined critical-infrastructure impacts, physical vulnerability, socioeconomic exposure to sea-level rise and flooding, flood-related business resilience, and coastal-agriculture pressures [31–36].

1.2 Geographic information system-based coastal vulnerability and research contribution

GIS-based approaches are well suited to coastal vulnerability assessment because demographic statistics, building inventories, productive land, ecosystem classes, and hazard polygons can be spatially aligned and evaluated at a common administrative scale. Coastal studies in Indonesia and other settings have demonstrated the value of GIS overlays for identifying tidal-flood footprints, assessing building exposure, and integrating multiple vulnerability indicators [1–4, 15–16]. At the same time, composite mapping can become difficult to audit when the underlying indicator values, weights, and monetary assumptions are not reported at the same level of detail. GIS has also been applied to population-pattern analysis, flood-process modeling, and flood-depth exposure assessment in other settings [37–39].

The contribution of this study is therefore not limited to producing a final vulnerability map. It links the four BNPB dimensions to village-level indicator tables, exposes the calculation pathway from individual indicators to the composite index, quantifies physical and economic exposure, and evaluates the robustness of rankings and housing-loss assumptions through sensitivity tests. The analysis is intentionally village-specific because the three adjacent coastal settlements differ markedly in population density, productive-land extent, facility exposure, and environmental

composition despite sharing the same broader coastal setting.

2. METHODOLOGY

2.1 Study area, data, and spatial workflow

The analysis covers Eretan Wetan (242.99 ha), Eretan Kulon (440.21 ha), and Kertawinangun (660.16 ha) in Kandanghaur Subdistrict, Indramayu Regency, West Java. Field observation recorded tidal-inundation conditions and coordinates of public and critical facilities. Demographic data were obtained from the Ministry of Home Affairs GIS platform, welfare data from Prodeskel, and agricultural, fisheries, and regional economic statistics from BPS. Building footprints were obtained from OSM, land use was manually interpreted from Google Earth Pro imagery, and administrative and tidal-flood hazard polygons were obtained from the Indramayu Regency government. Spatial clipping, overlay, scoring, and mapping were conducted in ArcGIS 10.3.

2.2 Hazard layer and spatial quality assurance/quality control

The tidal-flood hazard layer was treated as a fixed secondary input supplied by the Indramayu Regency government; it was not independently generated in this study from a digital elevation model (DEM) or a hydrodynamic tide simulation. The project archive does not preserve the DEM source/year, spatial resolution, vertical datum, or tidal-water-level scenario used to create the governmental polygons. No independent land-subsidence raster or correction term was added during the vulnerability analysis. Consequently, land subsidence is represented only if it had already been embedded in the source hazard product. The results should therefore be interpreted as a comparative vulnerability assessment conditioned on the supplied hazard zonation, not as a dynamic forecast of future inundation depth. The data sources, processing procedures, and quality assurance/quality control (QA/QC) status used in the analysis are summarized in Table 1.

Table 1. Data sources, processing, and quality assurance/quality control (QA/QC) status

Data Layer	Source / Processing	QA/QC Statement
Tidal-flood hazard	Indramayu government secondary polygons	Area reconciliation; DEM/tide metadata not archived
Socioeconomic tables	Kemendagri GIS, Prodeskel, BPS	Population, ratio, welfare, and value calculations recomputed
Buildings	OSM footprints; clip/overlay by hazard class	Count reconciliation; unclassified residuals reported
Land use	Manual Google Earth Pro interpretation	Productive and BNPB environmental classes; area checks

Note: The archived project files do not record the OSM extraction timestamp, Google Earth image acquisition date, or minimum mapping unit; these metadata limitations are stated rather than reconstructed. BNPB = Indonesian National Disaster Management Agency, GIS = geographic information system, OSM = OpenStreetMap, DEM = digital elevation model, QA/QC = quality assurance/quality control.

A basic internal QA/QC check was added for editable spatial inputs. Hazard-class areas sum exactly to the reported village areas. OSM building totals were compared with hazard-class intersections: classified counts equal 4,037 of 4,039 buildings in Eretan Wetan, 3,845 of 3,865 in Eretan Kulon, and 1,837 of 1,852 in Kertawinangun. The small residuals (2, 20, and 15 buildings) are treated as boundary/no-data intersections rather than silently assigned to a class. Public and critical facilities were checked against field-recorded coordinates. Land-use interpretation used explicit

classes (agriculture, aquaculture, protected forest, natural forest, mangrove, shrubland, and wetland/swamp), but the source archive does not retain the image date or an independent accuracy sample; this remains a limitation.

2.3 Vulnerability indicators and aggregation

The indicator framework follows BNPB Regulation No. 2/2012 and the InaRISK methodology. Each indicator is classified as low (score 0.33), medium (0.67), or high (1.00).

Social vulnerability combines population density (60%) with sex ratio, vulnerable-age ratio, poverty ratio, and disability ratio (10% each). Economic vulnerability combines productive-land value (60%) and estimated village agricultural/fishery gross regional domestic product (GRDP) (40%). Physical vulnerability combines housing loss (40%), public-facility loss (30%), and critical-facility loss (30%). Environmental vulnerability combines protected forest (10%), natural forest (30%), mangrove (40%), shrubland (10%), and wetland/swamp (10%).

The BNPB/InaRISK social table assigns the sex-ratio classes >40 (low), 20-40 (medium), and <20 (high). In the project worksheet, sex ratio is explicitly calculated as male population divided by female population x 100, producing 104, 102, and 101. These are conventional demographic-style ratios, whereas the BNPB breakpoints are unusual for such values. To avoid ambiguity, the revised manuscript reports both the formula and the resulting class and refers to this variable as the "BNPB operational sex-ratio indicator" rather than presenting the thresholds without explanation.

The composite vulnerability index is calculated as $V = 0.40S + 0.25P + 0.25E + 0.10N$, where S, P, E, and N are the social, physical, economic, and environmental indices. These weights are taken from the BNPB flood-vulnerability framework and are therefore policy-standard weights rather than study-specific preferences.

For the social dimension, population density is calculated as population divided by village area. The operational sex ratio is male population divided by female population and multiplied by 100. The vulnerable-age ratio compares the combined population aged under 14 years and over 64 years with the population aged 15-64 years; poverty and disability indicators are expressed as proportions of the relevant village population or household base. Each indicator is classified using the BNPB operational classes and multiplied by its assigned weight before summation. Reporting the underlying ratios alongside their weighted contributions is important because the sex-ratio breakpoints differ from conventional demographic interpretation.

For economic vulnerability, productive-land value is derived from agricultural and aquaculture areas and their sector values, while the village agricultural/fishery GRDP proxy is estimated by distributing the regency sector GRDP according to village area in the project calculation. Exposure in low-, medium-, and high-hazard classes is represented by influence factors of 0%, 50%, and 100%, respectively. This treatment converts spatial overlap into a comparable monetary exposure proxy while retaining the BNPB weighting of 60% for productive land and 40% for the GRDP indicator.

For physical vulnerability, housing exposure is the sum of building counts in each hazard class multiplied by the corresponding proxy unit loss. Public and critical facility exposure is calculated from mapped floor area, the assigned unit value per square metre, and the hazard-class influence factor. Environmental vulnerability is calculated from the mapped area of protected forest, natural forest, mangrove, shrubland, and wetland/swamp within each village and then weighted according to the BNPB framework. These calculations ensure that the four dimensions are derived independently before the composite weighting is applied.

2.4 Monetary exposure and uncertainty

The source calculation assigns housing proxy losses of IDR

5 million, IDR 10 million, and IDR 15 million per building in low-, medium-, and high-hazard zones. The project report attributes this schedule to BNPB Regulation No. 2/2012. Because the archived worksheet does not document a local 2025 replacement-cost schedule or a distinct price base year, the values are treated here as scenario-based proxy losses, not contemporary market replacement costs. Public facilities are valued at IDR 3 million/m²; health facilities at IDR 4 million/m²; and economic critical facilities at IDR 2 million/m². Medium-hazard facility values are multiplied by 50% and high-hazard values by 100%.

Uncertainty in the housing assumption is illustrated with a deterministic $\pm 20\%$ test while holding public-facility, critical-facility, and economic estimates constant. This is a sensitivity range, not a statistical confidence interval.

2.5 Weight sensitivity analysis

A one-at-a-time (OAT) sensitivity test changes each baseline component weight by $\pm 10\%$ relative to its original value and then renormalizes all four weights to sum to 1.00. Eight alternative weighting scenarios are evaluated. Composite scores and rankings are recalculated from the exact component indices reported below.

The sensitivity tests are designed as robustness checks rather than probabilistic uncertainty models. The $\pm 10\%$ OAT test examines whether the final village ordering depends excessively on any single BNPB component weight, while the $\pm 20\%$ housing-cost test illustrates the effect of a plausible deterministic perturbation in the largest physical-loss component. These tests do not substitute for empirical probability distributions, local depth-damage functions, or a full Monte Carlo analysis; instead, they make the consequences of the main modeling assumptions visible to readers and decision-makers.

3. RESULTS AND DISCUSSION

3.1 Tidal-flood hazard distribution

The supplied hazard layer shows that high-hazard areas dominate Eretan Wetan and Eretan Kulon, whereas Kertawinangun is dominated by the medium class. The three hazard classes reconcile exactly with each village area, providing a basic geometry-completeness check.

The spatial contrast is substantial. More than half of Eretan Wetan (55.26%) and Eretan Kulon (54.24%) falls within the high-hazard class, whereas 84.01% of Kertawinangun is classified as medium hazard and only 14.16% as high hazard. This pattern is consistent with the broader exposure of low-lying northern Java coastal settlements to recurrent tidal inundation reported in previous Indonesian [1-4]. The two Eretan villages therefore combine direct coastal proximity with a larger share of high-hazard land, while Kertawinangun experiences a wider but generally lower-intensity mapped hazard footprint.

Hazard class alone, however, does not determine the composite vulnerability result. Kertawinangun illustrates this distinction: its hazard map is dominated by the medium class, yet its extensive agricultural and aquaculture assets produce the largest economic exposure of the three villages. Conversely, the Eretan villages combine high-hazard coverage with dense settlements and critical facilities. This confirms the

analytical value of separating the hazard layer from the four vulnerability dimensions rather than treating mapped inundation as a direct surrogate for overall disaster

vulnerability. The village-level hazard areas are summarized in Table 2, while the spatial distribution is shown in Figure 1.

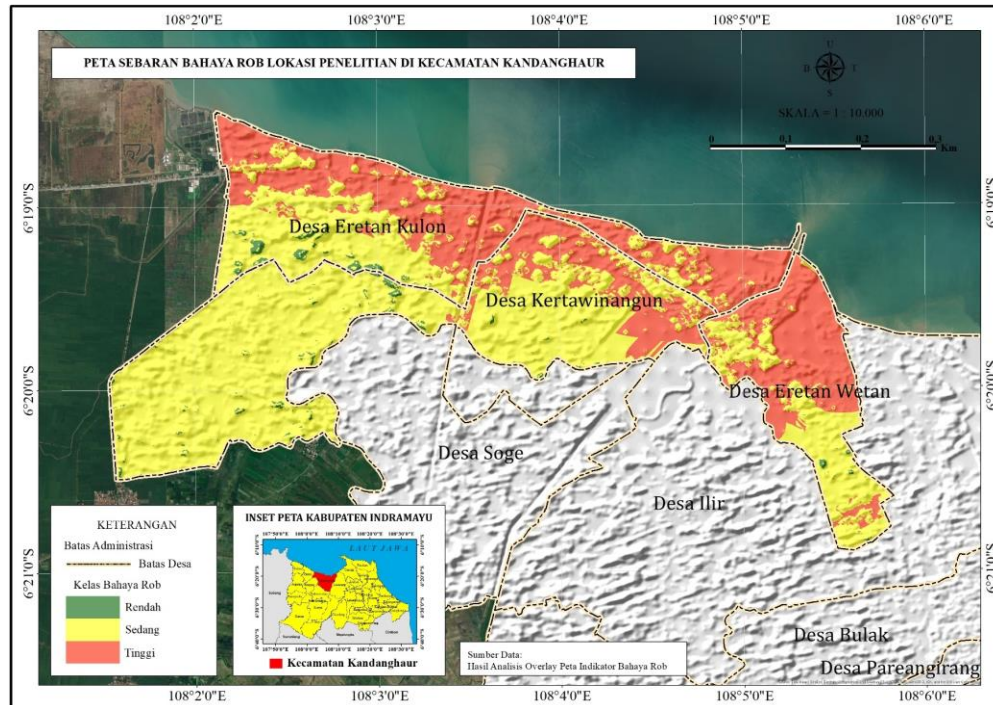


Figure 1. Tidal-flood hazard distribution in the study villages

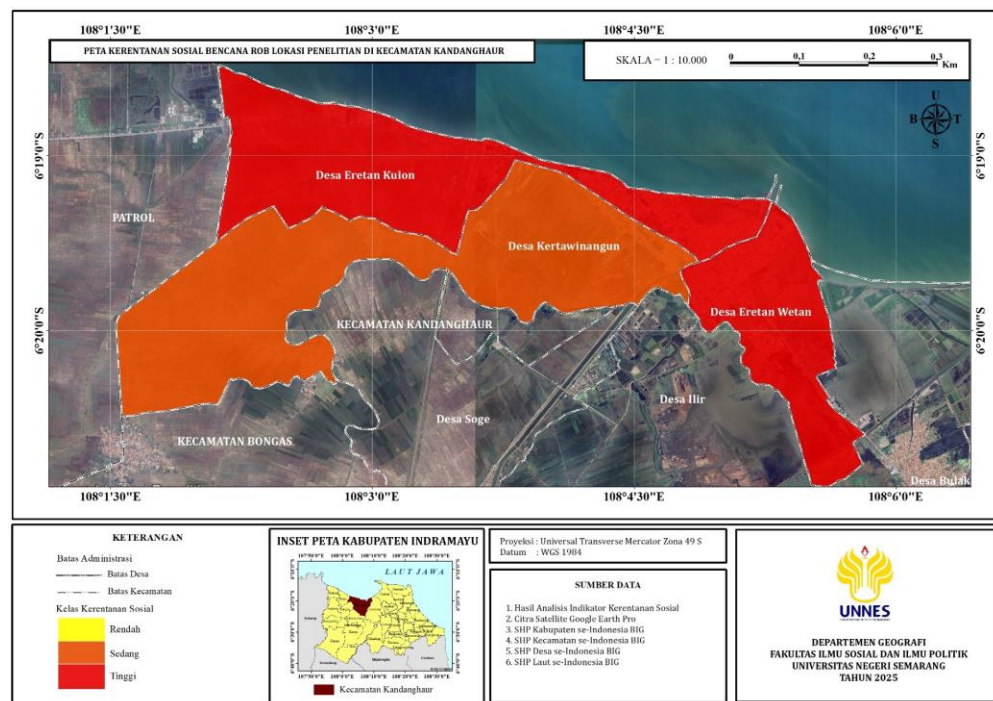


Figure 2. Social vulnerability map

Table 2. Tidal-flood hazard area by village

Village	Low	Medium	High
Eretan Wetan	1.52 ha (0.63%)	107.20 ha (44.12%)	134.27 ha (55.26%)
Eretan Kulon	10.00 ha (2.27%)	191.45 ha (43.49%)	238.76 ha (54.24%)
Kertawinangun	12.08 ha (1.83%)	554.59 ha (84.01%)	93.49 ha (14.16%)

3.2 Social vulnerability

Social vulnerability is highest in the two coastal Eretan villages because population density and poverty dominate the weighted index. Eretan Wetan also has a high vulnerable-age ratio. Kertawinangun is classified as medium because its lower population density reduces the 60% density contribution. The social index for Eretan Kulon is 0.833, obtained directly from

the five indicator contributions shown in Table 3; presenting those contributions makes the village-level score fully traceable.

Table 3. Social indicators and weighted contributions by village

Indicator	Eretan Wetan	Eretan Kulon	Kertawinangun
Population density	53 H; 0.600	26 H; 0.600	9 M; 0.400
BNPB sex ratio	104 L; 0.033	102 L; 0.033	101 L; 0.033
Vulnerable-age ratio	41 H; 0.100	40 M; 0.067	40 M; 0.067
Poverty ratio (%)	71.45 H; 0.100	71.19 H; 0.100	65.94 H; 0.100
Disability ratio (%)	0.101 L; 0.033	0.210 L; 0.033	0.195 L; 0.033
Social index / class	0.866 / High	0.833 / High	0.633 / Medium

Note: H = high, M = medium, L = low; values after semicolons are weighted contributions.

Population density is the strongest differentiating social indicator because it carries a 60% weight. Eretan Wetan reaches 53 persons/ha and Eretan Kulon 26 persons/ha, both classified as high, whereas Kertawinangun records 9 persons/ha and is classified as medium. The difference substantially lowers Kertawinangun's social index despite all three villages having high poverty ratios. Eretan Wetan also records a vulnerable-age ratio of 41, compared with 40 in Eretan Kulon and Kertawinangun, reinforcing the concentration of residents who may require additional assistance during evacuation and recovery.

From a disaster-management perspective, high social vulnerability means that an equivalent flood footprint can create different demands for evacuation support, temporary shelter, health services, livelihood assistance, and post-disaster recovery. This interpretation is consistent with multidimensional vulnerability research, which emphasizes that demographic structure and socioeconomic disadvantage shape the capacity to anticipate, cope with, and recover from hazards [10, 11, 12]. The sex-ratio indicator contributes only 0.033 in each village under the BNPB operational classification, so the social differences observed here are driven principally by density, poverty, and vulnerable age rather than by sex ratio. The resulting spatial pattern of social vulnerability is shown in Figure 2.

3.3 Economic vulnerability

Economic vulnerability is high in all three villages. Productive land is heavily exposed to medium and high tidal-flood classes, and the estimated agricultural/fishery GRDP exceeds the BNPB high-class threshold in every village. Kertawinangun has the largest economic exposure because of its extensive agricultural and aquaculture area.

The economic results reveal a different spatial ordering from the social dimension. Productive-land exposure rises from IDR 11.216 billion in Eretan Wetan to IDR 24.925 billion in Eretan Kulon and IDR 43.131 billion in Kertawinangun. The estimated village agricultural/fishery GRDP follows the same direction, from IDR 10.679 billion to IDR 19.594 billion and IDR 25.110 billion. Consequently, Kertawinangun has the highest combined economic exposure

(IDR 68.240 billion) even though its social and physical indices are lower than those of the Eretan villages. The corresponding economic indicators and exposure values are summarized in Table 4.

Table 4. Economic indicators and exposure by village

Indicator	Eretan Wetan	Eretan Kulon	Kertawinangun
Productive-land value	IDR 11.216 bn H; 0.60	IDR 24.925 bn H; 0.60	IDR 43.131 bn H; 0.60
Village GRDP estimate	IDR 10.679 bn H; 0.40	IDR 19.594 bn H; 0.40	IDR 25.110 bn H; 0.40
Economic index / class	1.000 / High	1.000 / High	1.000 / High
Economic exposure	IDR 21.895 bn	IDR 44.519 bn	IDR 68.240 bn

This finding demonstrates why productive-land exposure should not be inferred solely from settlement density or the proportion of high-hazard land. Large agricultural and aquaculture areas can generate substantial livelihood risk under recurrent medium-hazard inundation, particularly when saline water affects crop productivity, pond management, access, and the timing of harvesting. The monetary values in Table 4 should therefore be interpreted as spatial exposure proxies for economic assets and activity, not as realized post-event losses. Their main analytical value is to identify where disruption to productive sectors could have the greatest consequences for local income and livelihood continuity. The spatial pattern of economic vulnerability is shown in Figure 3.

3.4 Physical vulnerability

Physical vulnerability is high in all villages. Housing and public-facility losses exceed the high-class thresholds throughout. Eretan Wetan and Eretan Kulon also contain critical facilities in high-hazard areas, whereas Kertawinangun has no critical facility in the mapped exposure inventory. The resulting Kertawinangun physical index is 0.799 rather than the rounded 0.79 used previously.

Table 5. Physical indicators, losses, and indices by village

Indicator	Eretan Wetan	Eretan Kulon	Kertawinangun
Housing loss	IDR 51.99 bn H; 0.40	IDR 53.04 bn H; 0.40	IDR 19.88 bn H; 0.40
Public facilities	IDR 14.00 bn H; 0.30	IDR 13.64 bn H; 0.30	IDR 8.79 bn H; 0.30
Critical facilities	IDR 2.11 bn H; 0.30	IDR 2.09 bn H; 0.30	IDR 0 L; 0.099
Physical index / class	1.000 / High	1.000 / High	0.799 / High
Physical exposure	IDR 68.10 bn	IDR 68.77 bn	IDR 28.67 bn

The housing inventory shows the concentration of built assets within mapped hazard zones. Eretan Wetan contains 4,039 OSM building footprints, of which 2,324 intersect the high-hazard class and 1,713 the medium class. Eretan Kulon contains 3,865 buildings, including 2,941 in high hazard, 883 in medium hazard, and 21 in low hazard. Kertawinangun contains 1,852 buildings, including 383 in high hazard, 1,375

in medium hazard, and 79 in low hazard. The small differences between total and classified OSM counts are explicitly retained as boundary/no-data residuals in the QA/QC procedure rather than forced into a hazard class. The corresponding physical indicators, loss estimates, and indices are summarized in Table 5.

Public-service exposure further strengthens the physical vulnerability of the study area. Field mapping recorded 26 public facilities in Eretan Wetan, 19 in Eretan Kulon, and 15

in Kertawinangun, including educational, religious, and administrative facilities. Eretan Wetan and Eretan Kulon also contain critical health or fish-marketing facilities within the mapped exposure inventory, while none was recorded for Kertawinangun. Damage or inaccessibility affecting such facilities can create indirect and cascading consequences by reducing emergency response capacity, interrupting basic services, and constraining local economic recovery [31]. The spatial pattern of physical vulnerability is shown in Figure 4.

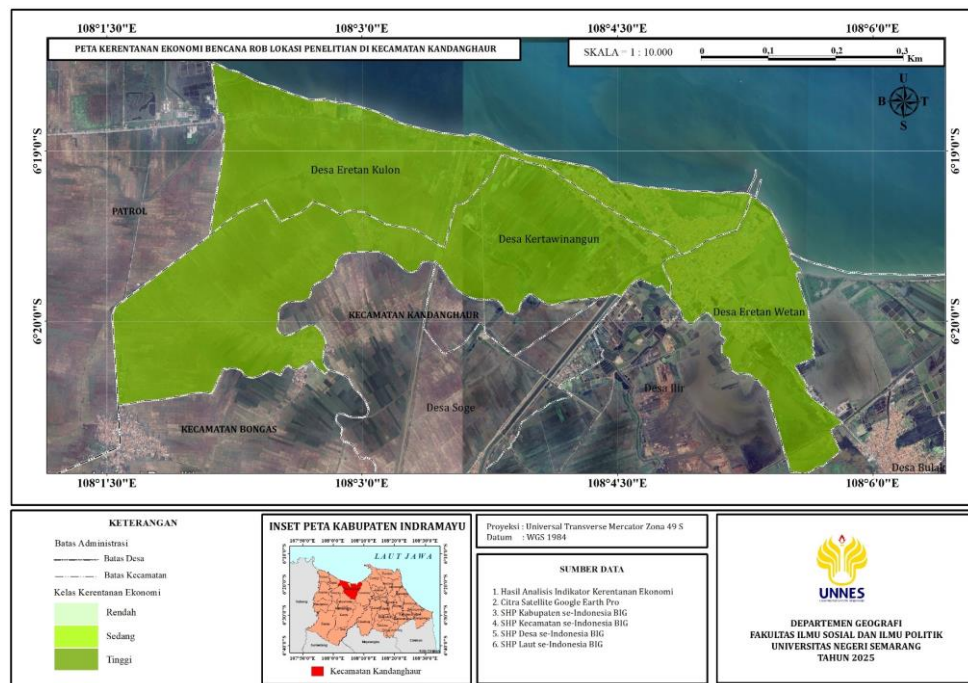


Figure 3. Economic vulnerability map

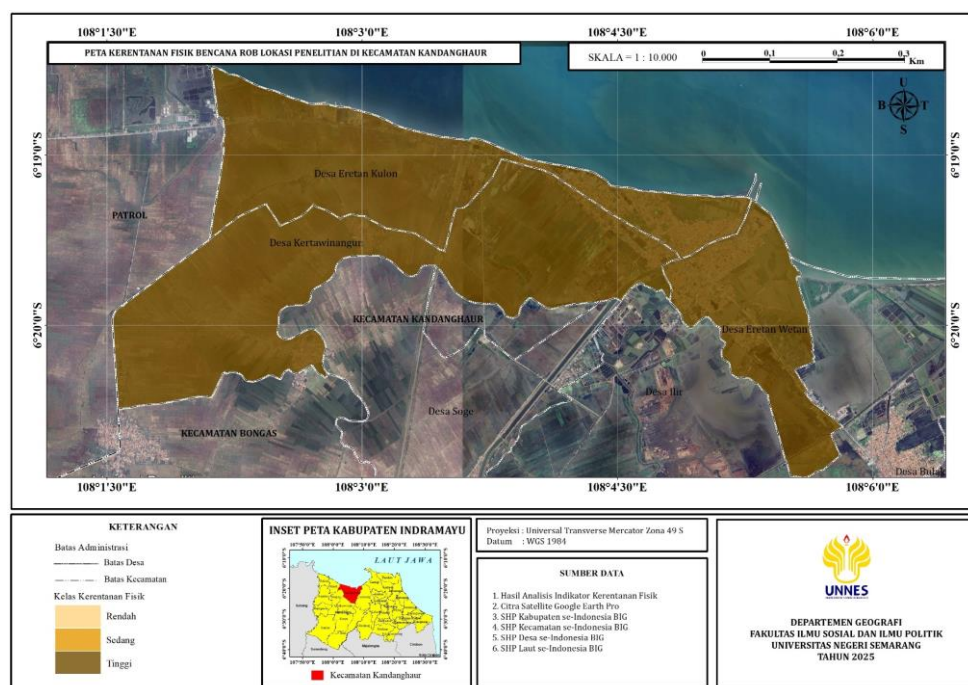


Figure 4. Physical vulnerability map

3.5 Environmental vulnerability

Environmental vulnerability is medium in all three villages.

Eretan Kulon has the highest index (0.529) because 12.09 ha of mangrove is in the medium class and 34.02 ha of shrubland is in the high class. Eretan Wetan and Kertawinangun both

score 0.363; their environmental indices are driven mainly by medium-class shrubland and low-class values for the remaining indicators.

Table 6. Environmental indicators and weighted contributions by village

Indicator	Eretan Wetan	Eretan Kulon	Kertawinangun
Protected forest	0 ha L; 0.033	0 ha L; 0.033	0 ha L; 0.033
Natural forest	0 ha L; 0.099	0 ha L; 0.099	0 ha L; 0.099
Mangrove	6.60 ha L; 0.132	12.09 ha M; 0.264	0 ha L; 0.132
Shrubland	24.36 ha M; 0.066	34.02 ha H; 0.100	23.40 ha M; 0.066
Wetland/swamp	0 ha L; 0.033	0 ha L; 0.033	0 ha L; 0.033
Environmental index	0.363 / Medium	0.529 / Medium	0.363 / Medium

The environmental index should be interpreted as the exposure of mapped environmental assets under the BNPB scoring framework rather than as a direct measure of

ecosystem quality or ecological degradation. For example, a larger mapped mangrove area increases the amount of environmental asset exposed and therefore contributes to the environmental vulnerability score, even though functioning mangroves can simultaneously reduce wave energy and support ecosystem-based disaster-risk reduction. This distinction is essential to avoid treating the presence of mangrove itself as environmentally harmful [40]. The corresponding environmental indicators and weighted contributions are summarized in Table 6.

Eretan Kulon has the highest environmental score because its 12.09 ha of mangrove falls in the medium class and its 34.02 ha of shrubland falls in the high class. Eretan Wetan has 6.60 ha of mangrove and 24.36 ha of shrubland, while Kertawinangun has no mapped mangrove and 23.40 ha of shrubland. The absence of protected forest, natural forest, and wetland/swamp in the mapped inventory keeps those indicators in the low class. Future ecological assessment would benefit from supplementing these area-based indicators with information on vegetation condition, continuity, shoreline position, and protective ecosystem function. The spatial pattern of environmental vulnerability is shown in Figure 5.

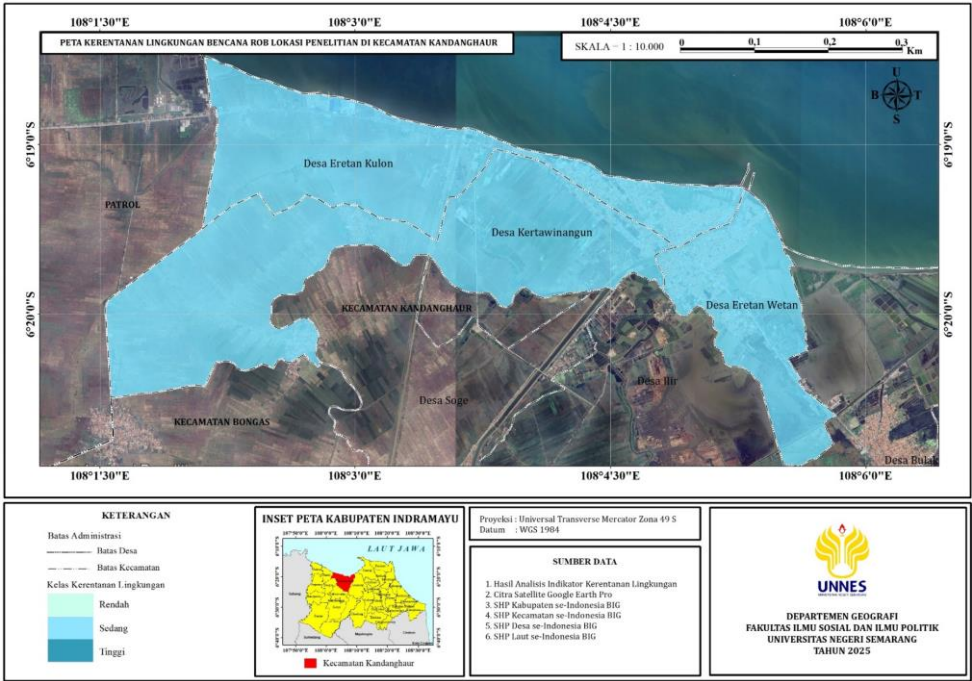


Figure 5. Environmental vulnerability map

3.6 Composite vulnerability and sensitivity

Aggregation of the transparent component tables produces composite scores of 0.886 for Eretan Kulon, 0.883 for Eretan Wetan, and 0.739 for Kertawinangun. All three remain in the high class. The small difference between Eretan Kulon and Eretan Wetan arises from the balance between social and environmental contributions, while Kertawinangun remains lower because of its medium social index and lower physical index. The component values and recalculated composite scores are summarized in Table 7.

Across the eight ±10% OAT weighting scenarios, the ranking remains Eretan Kulon > Eretan Wetan > Kertawinangun. The score ranges are 0.878-0.888 for Eretan

Wetan, 0.883-0.890 for Eretan Kulon, and 0.733-0.746 for Kertawinangun. The rank is robust within this test, but the Eretan Kulon-Eretan Wetan gap remains very small (approximately 0.002-0.005), so the top two villages should be treated as nearly tied for prioritization.

The sensitivity result is important for interpretation because the difference between the two highest-ranked villages is very small. A strict ordinal reading would place Eretan Kulon first and Eretan Wetan second, but the baseline difference is only 0.003 and remains narrow across the tested scenarios. For planning purposes, the two villages are therefore better treated as a shared highest-priority group rather than as meaningfully different risk tiers. Their intervention needs nevertheless differ: Eretan Wetan has the higher social index, whereas

Eretan Kulon has the higher environmental index.

Table 7. Recalculated composite vulnerability

Component	Eretan Wetan	Eretan Kulon	Kertawinangun
Social (w = 0.40)	0.866	0.833	0.633
Physical (w = 0.25)	1.000	1.000	0.799
Economic (w = 0.25)	1.000	1.000	1.000
Environmental (w = 0.10)	0.363	0.529	0.363
Composite score	0.883	0.886	0.739
Class / rank	High / 2	High / 1	High / 3

Kertawinangun remains third in every weighting scenario, but a lower composite score should not be interpreted as low concern. Its composite value of 0.739 is still within the high vulnerability class, and its economic exposure is the largest of all three villages. The component-level interpretation therefore prevents a common limitation of composite indices: a single final number can conceal severe vulnerability within one dimension even when the overall ranking is lower. Transparent reporting of the component indices is consequently necessary for selecting interventions that correspond to the actual drivers in each village. The sensitivity-test ranges and rank stability are summarized in Table 8, and the composite vulnerability pattern is shown in Figure 6.

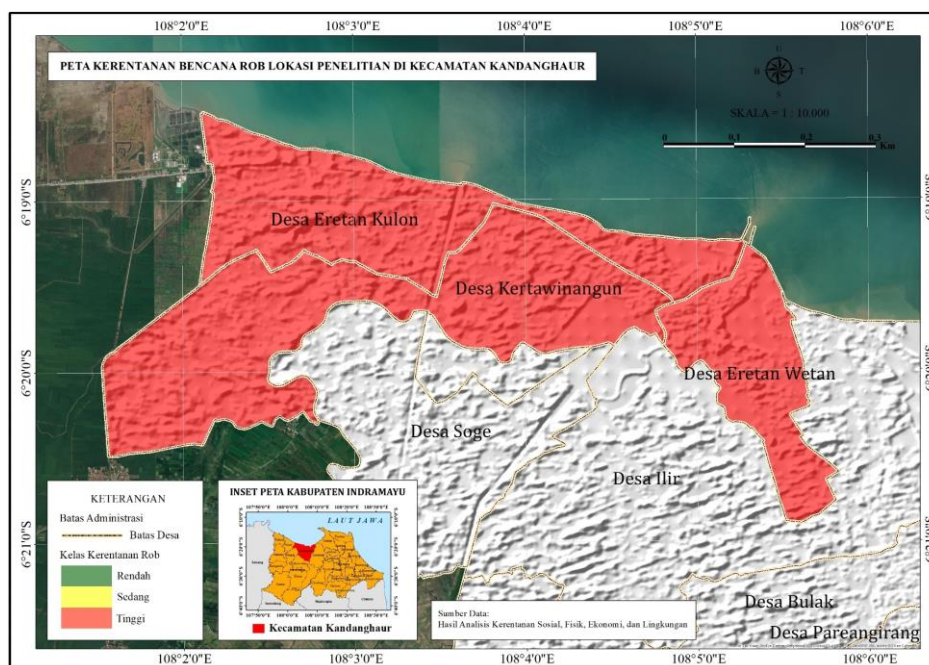


Figure 6. Composite tidal-flood vulnerability map

Table 8. Summary of $\pm 10\%$ weight sensitivity test

Village	Baseline	Scenario Range	Rank Stability
Eretan Wetan	0.883	0.878-0.888	Rank 2 in all scenarios
Eretan Kulon	0.886	0.883-0.890	Rank 1 in all scenarios
Kertawinangun	0.739	0.733-0.746	Rank 3 in all scenarios

3.7 Financial exposure and housing-cost uncertainty

The detailed village calculations yield combined physical and economic exposure of approximately IDR 300.2 billion, comprising about IDR 165.54 billion in physical exposure and IDR 134.65 billion in economic exposure. Because the housing schedule is a proxy rather than a documented 2025 replacement-cost schedule, the estimate should be interpreted as scenario-based exposure rather than a market-value damage forecast.

The uncertainty range shows that housing-price assumptions can shift the study-area total by approximately IDR 25 billion in either direction. A future update should replace the proxy schedule with an official Indramayu replacement/repair cost standard and, where possible, a flood-

depth damage function.

Table 9. Financial exposure under $\pm 20\%$ housing-unit-cost sensitivity

Village	Baseline Total	Housing - 20%	Housing +20%
Eretan Wetan	IDR 89.99 bn	IDR 79.59 bn	IDR 100.39 bn
Eretan Kulon	IDR 113.28 bn	IDR 102.67 bn	IDR 123.89 bn
Kertawinangun	IDR 96.91 bn	IDR 92.93 bn	IDR 100.89 bn
Study area	IDR 300.18 bn	IDR 275.20 bn	IDR 325.16 bn

Note: Only housing unit values are varied; all public-facility, critical-facility, and economic values are held constant. Totals use the rounded values reported in the project calculation tables.

The $\pm 20\%$ test changes the study-area total from IDR 275.20 billion to IDR 325.16 billion, indicating that the housing-cost assumption materially affects the headline exposure estimate but does not alter the qualitative conclusion that the three villages contain substantial exposed assets. Eretan Kulon retains the largest baseline combined exposure (IDR 113.28 billion), followed by Kertawinangun (IDR 96.91

billion) and Eretan Wetan (IDR 89.99 billion). These totals combine different asset categories and should be used for comparative screening and prioritization rather than for compensation, insurance, or engineering replacement-cost decisions. The baseline and $\pm 20\%$ housing-unit-cost scenarios are summarized in Table 9.

3.8 Planning implications and study limitations

The multidimensional results suggest differentiated priorities across the three villages. In Eretan Wetan, the combination of the highest social vulnerability and very high physical exposure supports measures that strengthen household preparedness, evacuation support for vulnerable groups, housing resilience, and continuity of public services. Eretan Kulon requires similarly strong settlement and facility protection, while its comparatively higher environmental score strengthens the case for mangrove management and restoration alongside land-use control. In Kertawinangun, livelihood protection and adaptation of agricultural and aquaculture systems deserve particular attention because economic exposure is high despite a lower social and physical score.

These priorities are consistent with the broader objectives of resilient and sustainable coastal settlement planning [41–43]. Reducing vulnerability requires more than structural flood protection: it also requires social protection, livelihood adaptation, protection of critical services, ecosystem-based measures, and spatial planning that limits additional exposure in recurrently inundated areas. Community preparedness and learning are also relevant because repeated tidal flooding is a chronic process that requires households and institutions to adapt to recurring disruption rather than respond only to isolated emergency events [40, 44–50].

Several limitations define the appropriate use of the results. First, the hazard polygons are a secondary governmental product whose DEM, vertical datum, tidal scenario, and production year are not preserved in the project archive; consequently, the analysis cannot be interpreted as a hydrodynamic simulation or future sea-level-rise forecast. Second, OSM extraction time, Google Earth imagery date, minimum mapping unit, and an independent land-use accuracy sample are unavailable. Third, the monetary estimates rely on BNBP/project proxy values rather than a documented local replacement-cost schedule. Fourth, the analysis is static and does not explicitly model temporal changes in land subsidence, shoreline dynamics, population growth, or future adaptation measures, all of which may alter coastal vulnerability over time [51].

Future research should therefore integrate a documented high-resolution elevation model, observed or modeled tidal levels, field-validated land-subsidence information, multi-temporal land-cover and building inventories, and locally verified repair or replacement costs. A depth-damage function and probabilistic uncertainty analysis would improve monetary estimates, while repeated village-level assessments could determine whether vulnerability is increasing or decreasing through time. These improvements would extend the present framework from a transparent baseline assessment toward a dynamic coastal risk-monitoring system.

3.9 Decision-use framework and monitoring priorities

For decision-making, the composite ranking should be used

together with the component profile rather than as a stand-alone priority list. Eretan Kulon and Eretan Wetan are effectively a shared highest-priority group because their composite scores differ by only 0.003, yet their dominant drivers are not identical. Eretan Wetan combines the highest social vulnerability with very high physical exposure, so monitoring should emphasize vulnerable-population distribution, household preparedness, service continuity, the condition of exposed housing, and the accessibility of public facilities during recurrent inundation. These indicators can be reassessed after major tidal-flood episodes to determine whether preparedness and physical-resilience measures are reducing practical vulnerability.

Eretan Kulon requires an equally integrated approach but with additional attention to environmental assets. Its high social and physical indices are accompanied by the highest environmental index in the study, reflecting the mapped extent of mangrove and shrubland under the BNBP area-based framework. Monitoring should therefore combine settlement and facility indicators with mangrove extent, vegetation condition, shoreline continuity, and evidence of erosion or ecosystem degradation. Because mangroves can provide protective functions while also being assets exposed to tidal flooding, management should distinguish between the quantity of mapped mangrove area and the ecological condition of that area. Restoration targets are more informative when they measure survival, density, connectivity, and shoreline protection rather than area alone [40].

Kertawinangun requires a different emphasis. Its medium social index and lower physical index reduce the composite score relative to the Eretan villages, but its economic exposure is the largest. This suggests that adaptation planning should track agricultural and aquaculture productivity, the duration and salinity of inundation, access to productive land, damage to pond infrastructure, and the recovery time of livelihood activities after tidal-flood events. Measures such as crop adaptation, pond-management adjustments, drainage improvement, access protection, livelihood diversification, and contingency support may therefore be as important as conventional structural protection. Monitoring economic recovery is especially important because repeated moderate inundation can create cumulative livelihood losses that are not visible in a single-event damage estimate.

A practical monitoring cycle can link these village-specific indicators to periodic updates of the GIS database. Administrative and demographic data can be refreshed annually or when new official statistics become available; OSM and land-use layers can be checked against more recent imagery and targeted field verification; exposed facilities can be re-surveyed after major infrastructure changes; and the hazard layer can be replaced when a better documented elevation- and tide-based product becomes available. This iterative approach would make the vulnerability assessment a living planning instrument rather than a one-time map. It also strengthens the connection with SDG 11 by supporting safer and more resilient settlements and with SDG 13 by providing an evidence base for locally targeted climate adaptation and disaster-risk reduction.

4. CONCLUSIONS

Village-level aggregation confirms high tidal-flood vulnerability across Eretan Wetan, Eretan Kulon, and

Kertawinangun. Eretan Kulon has the highest composite score (0.89), followed very closely by Eretan Wetan (0.88), while Kertawinangun scores 0.74. The four dimensions show distinct drivers: social vulnerability is high in both Eretan villages and medium in Kertawinangun; economic and physical vulnerability are high throughout; and environmental vulnerability is medium in all three villages. The symmetric indicator tables make these results directly traceable.

The $\pm 10\%$ weight test preserves the village ranking, although the first two villages are nearly tied. Combined physical and economic exposure is approximately IDR 300.2 billion, and the $\pm 20\%$ housing-cost test widens the plausible scenario range to about IDR 275.2-325.2 billion. Interpretation of this monetary estimate should remain cautious because the local price base year and replacement-cost standard were not preserved in the source archive. The hazard result is also conditional on a secondary governmental zonation whose DEM and tidal-scenario metadata are unavailable. Priority actions include strengthening housing and public services in high-hazard corridors, protecting productive livelihoods, restoring mangrove buffers, and improving the metadata and validation protocols used in future village-scale vulnerability assessments.

The principal significance of the study is that the same high composite class represents different vulnerability structures across adjacent villages. Making those structures visible is more useful for planning than relying on the composite map alone. The approach provides a reproducible baseline for village-scale coastal adaptation while also identifying the specific data improvements required for future hazard and damage modeling.

ACKNOWLEDGMENT

This work was supported by the DPA of the Institute for Research and Community Service, Universitas Negeri Semarang (LPPM UNNES), under Research Contract No. 761.14.3/UN37/PPK.11/2025. Administrative maps, secondary data, and fieldwork support were provided by relevant agencies of Indramayu Regency and village authorities in Eretan Wetan, Eretan Kulon, and Kertawinangun.

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NOMENCLATURE

V	Composite vulnerability index
S	Social vulnerability index
P	Physical vulnerability index
E	Economic vulnerability index
N	Environmental vulnerability index