

Article

High-Resolution Coastal Vulnerability Assessment for the Istrian Peninsula: Developing a Physical Coastal Vulnerability Index (PCVI)

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Abstract: Increasing risks from sea-level rise and other climate impacts call for a focus on physical coastal attributes, emphasising the need for region-specific tools to address the vulnerability of different coastlines. This paper presents the development of a Physical Coastal Vulnerability Index (PCVI) for climate change impacts like sea-level rise, erosion, and storm surges, which is applied to the Croatian coast of the Istrian Peninsula. The methodology provides a detailed, site-specific vulnerability assessment focusing on physical parameters such as coastal aspect, slope, elevation, and coastal type. Eight different grid cell sizes were evaluated to map the coastline, demonstrating, as expected, that smaller cells (5 × 5 m) captured more detailed variability in vulnerability. Among seven evaluated calculation methods, the second root of the self-weighted arithmetic mean (M3) proved the most effective, emphasising high-risk regions by prioritising critical physical variables. The results show that the western Istrian coast is more vulnerable due to its morphological properties, with nearly 50% of highly vulnerable coastlines. This paper emphasises the importance of using high-resolution grids to avoid oversimplification of vulnerability assessment and recommends using PCVI as a basis for further socio-economic assessments. The proposed PCVI methodology offers a framework that can be adapted to assess the physical vulnerability of the eastern Adriatic coast and other similar coastal regions, particularly in the Mediterranean, enhancing its relevance for integrated coastal zone management and global climate change mitigation strategies.

Keywords: coastal vulnerability; sea-level rise; climate change impacts; Adriatic coast



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1. Introduction

Coastal regions worldwide are increasingly vulnerable to the impacts of climate change, including sea-level rise, increased frequency of extreme weather events, and accelerated erosion [1,2]. These impacts endanger natural ecosystems and threaten the socio-economic systems that rely on them. Addressing the vulnerability of coastal areas has become a pressing priority for environmental scientists and policymakers [3]. Coastal vulnerability refers to the socio-economic elements at risk from coastal hazards, such as sea-level rise, coastal storms, and erosion. The current understanding of coastal vulnerability examines the complex interactions between the spatial distribution of these hazards and the exposed socio-economic elements. Contemporary studies emphasise that coastal vulnerability is geographically dependent [4]. Assessing coastal vulnerability involves

understanding both the physical attributes of the coast and the socio-economic factors that influence the resilience of the local population [5–12].

The Croatian part of the Istrian Peninsula (Figure 1), located in the northern Adriatic Sea, is a unique case for assessment due to its complex coastal morphology, varying degrees of urbanisation, diverse economic activities, and rich cultural heritage [13,14]. This uniqueness makes it an ideal case study for understanding the complexities of coastal vulnerability assessments. Like other western Mediterranean coastal areas [15], the Istrian coast faces significant challenges from climate change, particularly concerning rising sea levels and the heightened frequency of storm surges [16,17]. Socio-economically, Istria is one of Croatia's most developed regions [18,19] and the most developed tourist county in Croatia, significantly contributing to the national budget [20]. The population is concentrated in coastal towns, which face increased pressure from urbanisation and infrastructure development [21].

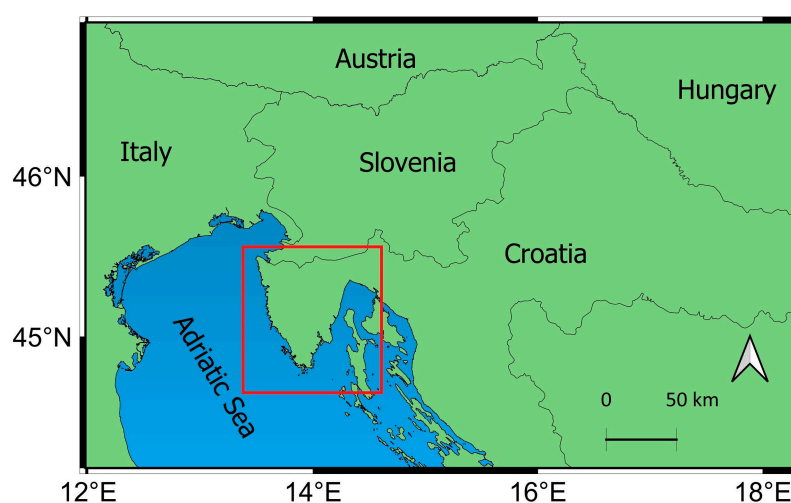


Figure 1. Study area—Istrian peninsula (red box).

Coastal vulnerability assessments usually involve evaluating physical factors, such as geomorphology, wave exposure, erosion potential, and socio-economic factors, including population density, economic activities, and infrastructure [7,22,23]. Socio-economic factors are a significant part of coastal vulnerability by underlining society's exposure and adaptive capacity in coastal areas. However, these factors contribute to the risk posed by climate change-related sea-level rise, erosion, coastal flooding, salinisation, and shoreline retreat. The number and type of variables used in coastal vulnerability analysis can vary based on location, the purpose of the analysis, the researcher's knowledge and experience, and data availability. Additionally, the relationships between coastal vulnerability variables differ from one index to another. Generally, calculating the Coastal Vulnerability Index can be categorised into three approaches: 1. In the first approach, all physical and socio-economic variables are combined into a single formula. 2. The second approach involves calculating the Coastal Vulnerability Index with two or three sub-indices. This method assesses physical and social vulnerability separately, and then a combined vulnerability index is created. 3. The third approach begins with assessing coastal physical vulnerability as a foundation for further analysis. This approach allows researchers to exclude areas of low vulnerability or those not of interest, thereby streamlining the analysis process. This method saves time and resources while focusing on areas of high vulnerability or significant importance [14].

This paper focuses on physical coastal vulnerability since physical factors predispose to coastal flooding, coastal erosion, and shoreline retreat intensity in the affected areas,

and influence socio-economic factors. In current research, authors use different calculation methods and consider diverse processes to collect, analyse, and represent coastal vulnerability data [14].

The objectives of this paper are threefold: (1) to determine the most appropriate cell dimensions for collecting, analysing, and representing coastal data, (2) to determine the most appropriate calculation methods which emphasise differences in vulnerability rather than averaging values, and (3) to conduct a physical coastal vulnerability analysis of the Croatian part of the Istria peninsula. In order to accomplish the paper's objective, the aim is to establish a methodological framework as a benchmark for coastal vulnerability assessments in the eastern Adriatic region as well as other Mediterranean and global coastal regions that are geologically and geomorphologically similar.

2. Theoretical Framework and Methodology

Statistical calculations and their visualisation were executed in Microsoft 365 Excel, while spatial calculations and map visualisation were performed in QGIS.org 3.34.2 Prizren [24].

2.1. Study Area

Our work focuses on the coast of the Istrian Peninsula, stretching from Luka Bay in the northeast to Rt Kamenjak (Cape Kamenjak) in the south and to the mouth of the Dragonja River in the northwest. A total of 607 km of coastline was analysed. The steep coast characterises the eastern coasts, while the western coasts of Istria feature gentler slopes (Figure 2). The western coast has been more developed than the eastern coast since Roman times [25]. Today, the western coast focuses more on tourism, whereas significant industrial facilities and passenger and cargo ports are located in the southern and eastern parts of the Istrian coast.

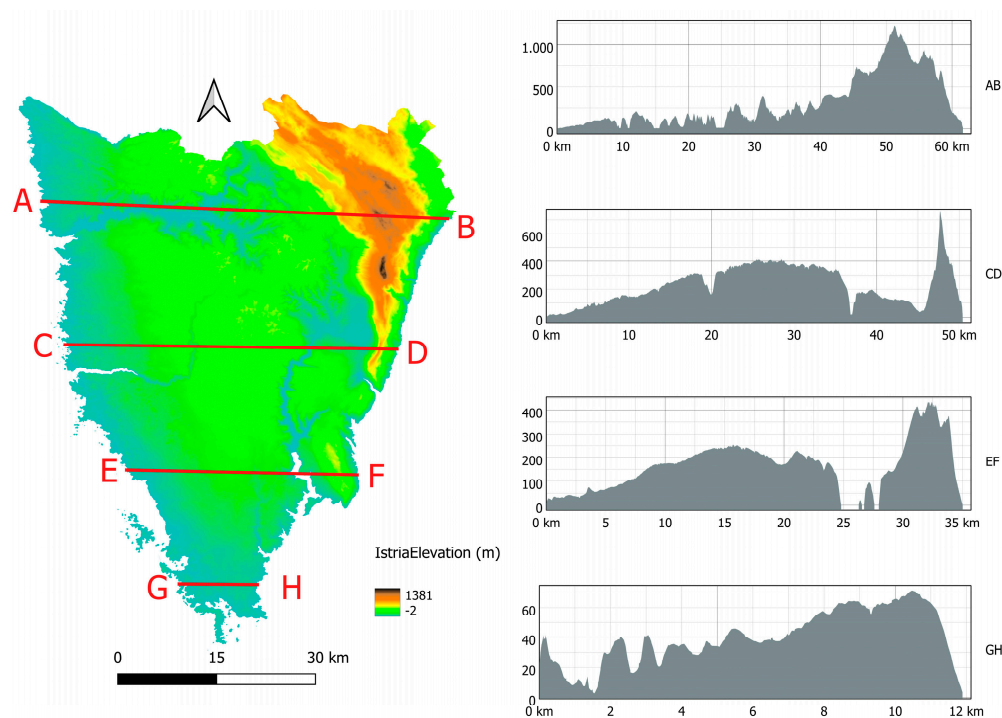


Figure 2. Istrian peninsula elevation with four elevation profiles.

Istrian coastal areas are divided among twenty-four municipalities, with Pula having the largest population of 52,220 and Funtana having the smallest population of 911 (Figure 3). While Istria and the eastern Adriatic coast are generally resilient to sea-level rise

due to the predominance of carbonate rocky coastlines and overall steep terrain, certain areas remain highly vulnerable to the effects of rising sea levels [26]. The eastern municipalities, with 48,876 inhabitants, are almost 2.5 times smaller than the western municipalities, with 121,298 inhabitants [27].

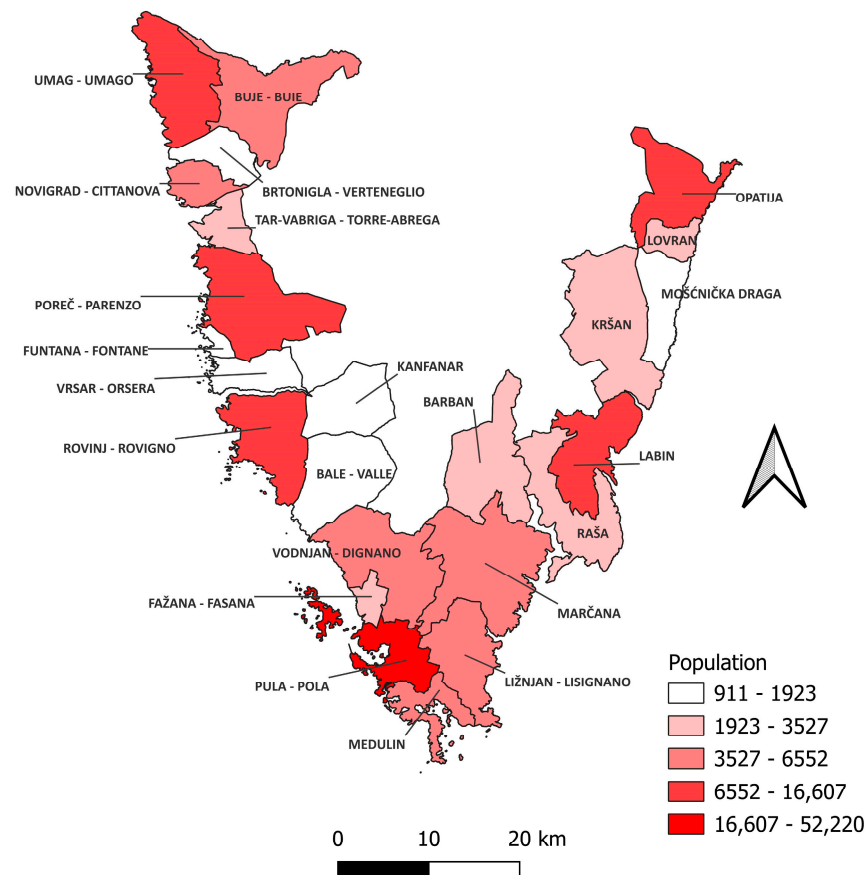


Figure 3. Coastal municipalities and population size.

2.2. Grid Cell Creation

One of this paper's objectives is to determine the most appropriate cell dimension for collecting, analysing, and representing coastal data. Choosing appropriate cell dimensions is crucial because it involves balancing two factors: a larger analysed area, which benefits from bigger cell dimensions, and the coastal type diversity of the Istrian coast, which calls for smaller cell dimensions. To achieve this objective, the analysed area of the Croatian part of the Istrian coast was divided into grids of eight different cell sizes: 5×5 m, 10×10 m, 25×25 m, 50×50 m, 100×100 m, 200×200 m, 500×500 m, and 1000×1000 m (Figure 4). These grids were created using the "Create grid" tool [24] based on the following extent: 45.523755651° N, 44.748733032° S, 14.354556892° E, 13.488774239° W. Coastal cells were then extracted from these grids using the "Select Layer by Location" tool [24], which compared them to the features from the layer containing the coastal line. The coastal line representing coastal (land) administrative borders was attained from the Register of Spatial Units of the Croatian State Geodetic Administration (CSGA) [28]. The selection of the most appropriate cell size was guided by physical coastal vulnerability variables, ensuring the scientific rigour of this research.

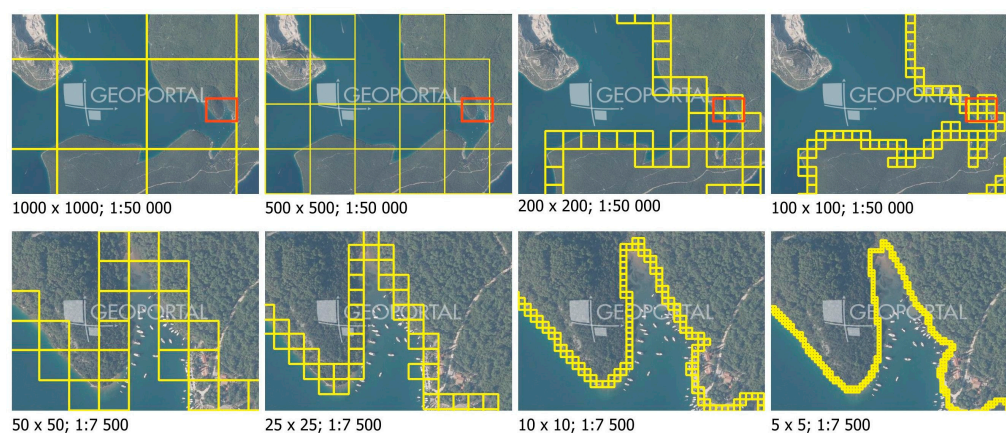


Figure 4. Different cell sizes (in meters) (yellow, grid cells;—red, enlarged area in the figure below; second row maps).

2.3. Optimising PCVI Calculation: Methodological Analysis and Justification

The Coastal Vulnerability Index (CVI) is the most frequently utilised method for assessing coastal vulnerability to sea-level rise, erosion, storm surges, and flooding [29]. The Physical Coastal Vulnerability Index (PCVI) is a tool designed to represent a large amount of different data related to coastal vulnerability using four key variables: coastal aspect, coastal slope, coastal height, and coastal type, to present a large amount of data. These variables are often used for assessing coastal vulnerability [14]. This paper evaluated seven methods to derive a single value that accurately represents physical coastal vulnerability, tailored explicitly for complex karstic coasts. One of the objectives was to identify a method that appropriately emphasises variables with higher values, indicating greater vulnerability, thereby resulting in a higher overall physical vulnerability. A practical approach involves using a modified central tendency measure favouring these higher, more critical values.

This paper demonstrates that measures of central tendencies do not provide real situations but average physical conditions, leading to overlooking vulnerable parts of the coast. While Equations (1) and (2), arithmetic mean (M1) and geometric mean (M2) are well-established measures of central tendency, this paper introduces five additional approaches, M3 to M7, to address the limitations of standard methods in highlighting vulnerable coastal areas. Equation (3) (M3) employs a self-weighting mechanism for physical variables, while Equation (4) (M4) incorporates weighted averages based on each variable's mean ranks of cell vulnerability. Equation (5) (M5), Equation (6) (M6), and Equation (7) (M7) represent modified arithmetic and geometric means. These methods emphasise higher vulnerability values and provide a more accurate representation of coastal risk, particularly in heterogeneous environments.

For the calculation methodology analysis, vulnerability rank values of 5×5 m dimension cells were used.

Equation (1). M1—Arithmetic mean.

$$PCVI = \frac{A + S + H + T}{4}, \quad (1)$$

Equation (2). M2—Geometric mean.

$$PCVI = \sqrt[4]{A \times S \times H \times T}, \quad (2)$$

Equation (3). M3—The second root of the self-weighted arithmetic mean.

$$PCVI = \sqrt{\frac{A^2 + S^2 + H^2 + T^2}{4}}, \quad (3)$$

Equation (4). M4—The second root of the weighted modified arithmetic mean. Weight represents the vulnerability variable mean value.

$$PCVI = \frac{A \times aa + S \times as + H \times ah + T \times at}{4 \times ta}, \quad (4)$$

Equation (5). M5—PCVI scores range between 0.5 and 12.5. Scores were divided into five equal bins and appropriate ranks from 1 to 5.

$$PCVI = \sqrt{\frac{A \times S \times H \times T}{4}}, \quad (5)$$

Equation (6). M6—PCVI scores range between 0.5 and 312.5. Scores were divided into five equal bins and appropriate ranks from 1 to 5.

$$PCVI = \sqrt{\frac{A^2 \times S^2 \times H^2 \times T^2}{4}}, \quad (6)$$

Equation (7). M7—PCVI scores range between 0.5 and 25. Scores were divided into five equal bins and appropriate ranks from 1 to 5.

$$PCVI = \frac{A^2 + S^2 + H^2 + T^2}{4} \quad (7)$$

In all equations:

PCVI—Physical Coastal Vulnerability Index

A—Coastal Aspect

S—Coastal Slope

H—Coastal Height

T—Coastal Type

aa—Mean Coastal Aspect Rank Level

as—Mean Coastal Slope Rank Level

ah—Mean Coastal Height Rank Level

at—Mean Coastal Type Rank Level

ta—Mean Rank Level of all Coastal Physical Variables

2.4. Morphometry and Morphology Analysis

A Digital Surface Model (DSM) of the CSGA with a 5 m resolution was used to calculate coastal height, slope, and aspect. Analysis with the “Zonal statistic” tool [24] was conducted separately for eight different cell sizes. Each analysed variable was assigned a relative vulnerability value based on its potential to contribute to physical changes caused by sea-level rise, storm surges, and waves. Although the Digital Terrain Model (DTM) would be the correct model to determine coastal slope, height, and aspect, the anthropogenic influence on some parts of the coast is significant. Representing anthropogenic landforms is critical in natural hazard assessments, as traditional DTMs may overlook these features, leading to misinterpretations [30]. Studies have shown that areas with significant human modifications, like the Amalfi Coast, exhibit increased vulnerability to hazards, which DSMs can effectively model [31]. In line with the established practice [14], this paper categorises coastal vulnerability into five distinct ranks: 1. very low vulnerability (blue), 2. low vulnerability (green), 3. moderate vulnerability (yellow), 4. high vulnerability (orange), and 5. very high vulnerability (red) (Table 1).

Table 1. Physical variables' vulnerability ranks.

Rank	Coastal Slope (°)	Coastal Aspect (°)	Coastal Height (m)	Type
1	>32	180–225	>0.60	High rocky coast (>40°)
2	12–32	135–180 and 225–270	0.45–0.60	Low rocky coast (<40°)
3	5–12	90–135 and 270–315	0.30–0.45	Low coast in clastic sediment (coarse-grained sediment)
4	2–5	45–90 and 315–360	0.15–0.30	Low coast in clastic sediment (fine-grained sediment)
5	0–2	0–45	0.0–0.15	Anthropogenically modified coast

2.4.1. Coastal Slope

Coastal slope is relevant to defining vulnerability to inundation and shoreline retreat. Coasts with low coastal slopes are more vulnerable to inundation, and face pronounced shoreline retreat speeds [32–34]. Coastal steepness was analysed using the “GDAL Slope” tool [35], and the results are displayed in degrees. Each cell was assigned a mean slope value obtained with the “Zonal Statistics” tool [24]. The ranks and ranges of the International Geographical Union (IGU) were used to define slope classes [36]. Slope values and associated ranks are shown in Table 1. The five slope vulnerability ranks, with rank 1 (>32°) representing very low vulnerability and rank 5 (0–2°) representing very high vulnerability, are closed bins with different intervals except rank one, which is an open bin. Bin size or intervals are inversely proportional to vulnerability.

2.4.2. Coastal Aspect

The coastal aspect important for exposure to predominant and strongest winds was calculated using the “Aspect” tool [24]. Each cell was assigned a mean aspect value obtained with the “Zonal Statistics” tool [24]. Rank values were determined using Croatia's Climate Atlas [37]. For this research, the annual wind rose for Rijeka station was used. With up to 30% of total wind annual occurrence and speed over 5.4 m/s from the north north east (NNE) sector [37], coastal aspects ranging from 0° to 45° were deemed the most vulnerable. Aspect values and associated ranks are shown in Table 1. The five aspect vulnerability ranks, with rank 1 (180–225°) representing very low vulnerability and rank 5 (0–45°) representing very high vulnerability, are closed bins with fixed bin size or interval of 45°. However, ranks 2, 3, and 4 necessitate two 45° intervals to represent the coastal aspect on antipodal points of the compass.

2.4.3. Coastal Height

Defining an average coastal height plays a critical role in identifying and valuing the vulnerability of coastal zones to sea-level rise, storm surges, and waves induced by climate change [6]. Each cell was assigned a mean elevation value obtained with the “Zonal Statistics” tool [24]. Coastal height vulnerability is based on a semi-empirical projection of the sea level change of the Adriatic Sea by the end of the 21st century. Under B1 [38,39], the most favourable climate scenario, conditions predict a sea-level rise of 62 ± 14 cm [40]. This value can be significantly amplified since the heights and return levels of positive and negative extremes are 50–100% more emphasised in Istria than in the middle and southern Adriatic [16]. Height values and associated ranks are shown in Table 1. Five height vulnerability ranks, with rank 1 (>60 cm) representing very low vulnerability and rank 5 (0–15 m) representing very high vulnerability, are closed bins with the same interval except rank 1, which is an open bin. Bin size or intervals are inversely proportional to vulnerability.

2.4.4. Coastal Type

To determine the type of coast, a combination of resources was utilised, such as Google Maps (with posted pictures, videos, and Street View), Google Earth Pro, Digital Orthophotos, OpenStreetMap, 1:25,000 topographic maps, and field research. Each 5×5 m cell was manually ranked based on a visual analysis of the coast. The division between vulnerability rank 1 and rank 2, concerning high and low rocky shores, was made using the coastal slope [41]. Low coast in clastic sediment (coarse-grained sediment) relates to all types of gravel and pebbles. Low coast in clastic sediment (fine-grained sediment) refers to sand, mud, and river mouths. Coastal areas composed of finer sediment particles are typically more susceptible to erosion due to the ease with which these smaller and lighter particles can be transported by dynamic coastal processes such as waves, currents, and wind. The reduced mass and cohesive properties of fine sediments allow them to be carried away, increasing the overall vulnerability of such areas to erosional forces [5,42,43]. The differentiation was made by analysing digital orthophotos and field research. Anthropogenically modified coast refers to a part of the coast that has been developed, whether it is a different type of port, artificial beach, promenade, or grey coastal protection infrastructure. Anthropogenically modified coasts were deemed the most vulnerable. Coastal types for bigger cell dimensions were determined by calculating the predominant vulnerability rank of the coastal types of each 5×5 m cell using the “Join Attributes by Location (Summary)” tool [24], where the attributes “intersect”, “overlap”, “contain”, and “are within” and the field to summarise were set to “majority” (Figure 5). Coastal type description and associated ranks are shown in Table 1.

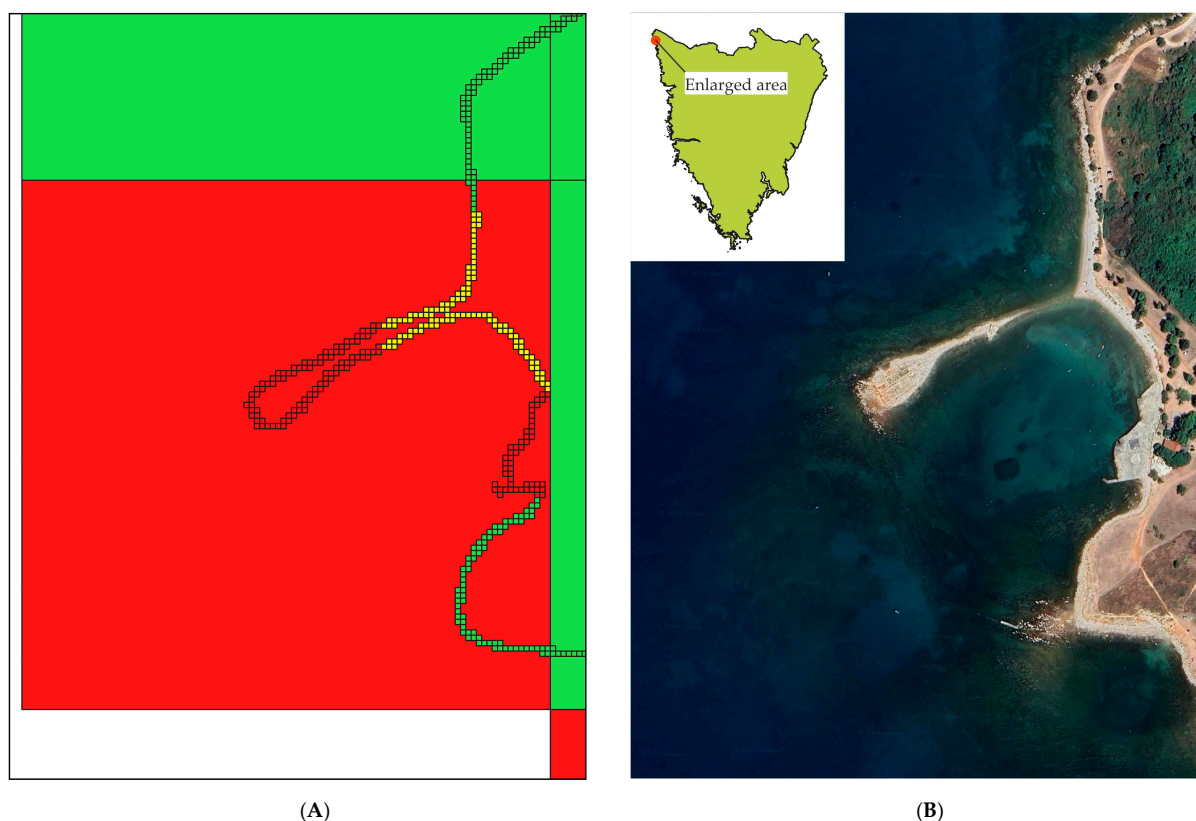


Figure 5. (A) Comparison of the coastal type vulnerability rank of different cell dimensions (5×5 m cells overlapped on 500×500 m cells. Colour of cells corresponds to vulnerability rank Table 1); (B) Satellite image of this part of the Istrian coast [44].

2.4.5. Physical Coastal Vulnerability Index (PCVI) Calculation

Equation (3) was used to calculate the PCVI. The results were calculated using 5×5 m dimension cells. The rationale for choosing the M3 methodology is given in the chapter on the PCVI Calculation Method.

3. Results and Discussion

The Istrian coast's physical vulnerability was analysed using different methods for PCVI calculation and different cell sizes. The obtained results provide a basis for comparing these methods' effectiveness and identifying areas with the highest level of vulnerability.

3.1. PCVI Calculation Method

Different calculation methods are used to assess coastal vulnerability. The most commonly used method for calculating the CVI, proposed by Gornitz, involves taking the square root of the product of the variables divided by the number of variables [22]. The calculation method and variables used can significantly influence vulnerability ranking. For this reason, a detailed analysis of seven calculation methods was conducted to determine the most appropriate one that emphasises differences in vulnerability rather than providing averaged values. This paper aimed to identify a calculation method resulting in a left-skewed distribution emphasising areas with higher vulnerability values rather than achieving a perfect Gaussian distribution. The analysis shows that, apart from method 6 (M6) (Figure 6), which deviates significantly from the Gaussian distribution, the other six calculation methods tend to follow the Gaussian distribution with varying skewness. The rationale for developing a calculation method favouring higher vulnerability is to avoid oversimplification or neglecting critical information.

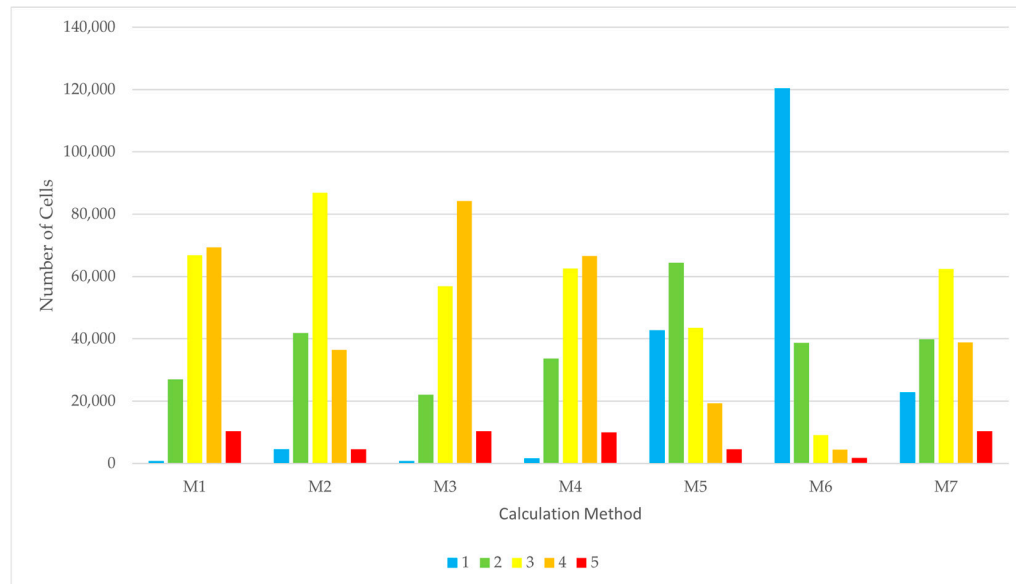


Figure 6. Vulnerability rank frequency by calculation methods.

Additionally, averaging masks vulnerability outliers, potentially underestimating significant risk areas. This simplification of coastal vulnerability may lead to misinterpretation of its true nature and to the development of ineffective mitigation strategies. Vulnerability ranks 4 and 5 show the highest cell share using the calculation method M3 (Figure 6), thus providing us with the needed calculation method that prioritises higher coastal vulnerability. Furthermore, the cell shares of the vulnerability ranks 2, 3, and 4 using the M3 calculation method exhibit an upward trend (Table 2).

Table 4. Cont.

Input Variable Vulnerability Rank				Calculation Method						
V1	V2	V3	V4	M1	M2	M3	M4	M5	M6	M7
3	3	3	3	3	3	3	3	2	1	2
4	4	4	4	4	4	4	4	4	3	4
5	5	5	5	5	5	5	5	5	5	5

3.2. Cell Dimensions

The aim of any research is the accurate presentation of results. For this reason, each research study adopts a different approach to data collection, calculation, and representation. For calculating CVI [33,45,46], coastal transects of different lengths are commonly used. Pantusa et al. (2018) [33] used 500 m transects, Ružič et al. (2019) [45] used 5 m transects, and Theocharidis et al. (2024) [46] used 100 m long transects. Kantamaneni (2016) [47] used 500×500 m manually placed cells, while Palmer et al. (2011) [8] used a combination of transects and 50×50 m cells. The administrative area is often used to calculate and represent socio-economic coastal characteristics [9,11,12]. Using the “Create grid” tool [24] speeds up placing cells along the analysed coast and prevents overlapping. However, this tool does not allow researchers to place the cells in a satisfactory location, i.e., to cover as much of the land as possible in relation to the sea. A comprehensive analysis of the results evaluates the effectiveness of different cell sizes, emphasising the importance of capturing spatial variability in coastal features (Figure 5). The findings are critically examined in this paper’s objective: determining the optimal grid resolution and providing insights into the physical vulnerability of the Istrian coastline. The results indicate significant regional differences in vulnerability, with the western coast showing higher vulnerability compared to the eastern coast. This disparity is attributed to the geomorphological features of the regions (Figure 2): the western coast’s lower elevation and gentle slopes increase susceptibility to flooding and erosion. In contrast, the eastern coast’s steeper slopes and higher elevations provide greater natural resilience. Future work could explore how localised anthropogenic activities, such as urbanisation and tourism development, exacerbate these natural vulnerabilities, particularly in areas like Brtonigla–Verteneglio (Table 8), which exhibits the highest share of rank five vulnerabilities.

3.2.1. Coastal Aspect Example

Most cell dimensions exhibit slightly right-skewed Gaussian distribution of vulnerability ranks, except for the 10×10 m and 1000×1000 m grids. Furthermore, higher vulnerability ranks show a downward trend with an increase in cell dimension, while lower vulnerability (resilient) ranks show an upward trend (Figure 7). A change in cell size does not show a pattern of change concerning coastline orientation. On the other hand, the average aspect value does not exhibit significant deviations in aspect value (Table 5). This analysis shows how cell dimensions influence the representation of vulnerability ranks, with smaller cells (e.g., 5×5 m) capturing finer-scale variability and larger cells leading to data homogenisation. The observed downward trend in higher vulnerability ranks and upward trend in lower (resilient) ranks with increasing cell size stresses the relevance of using smaller grids to identify high-risk areas accurately. While the lack of significant changes in average aspect values suggests consistency in this variable across scales, the differences in rank distribution align with this paper’s aim to identify optimal cell dimensions for precise coastal data representation. Such results contribute directly to the proposed methodological framework, demonstrating the utility of high-resolution grids for capturing spatial variability, particularly in regions with complex geomorphology like the Istrian coast.

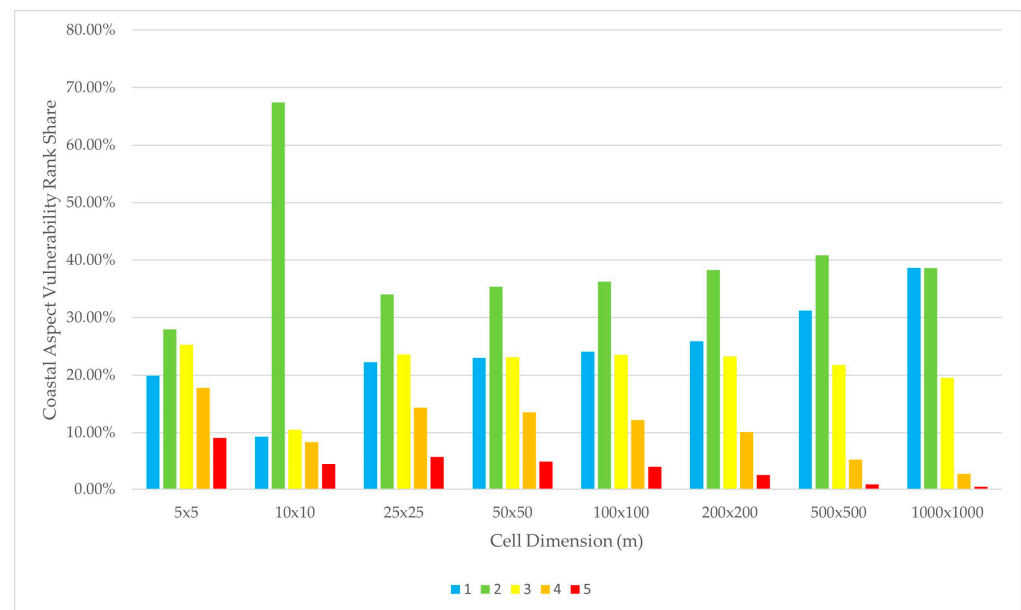


Figure 7. Coastal aspect vulnerability rank share by different cell dimensions.

Table 5. Cell statistics.

Cell Description			Aspect (°)			Slope (°)			Height (m)			Type		
Cell Size (m)	Number of Cells	Total Area (km ²)	Min Value	Max Value	Mean Value	Min Value	Max Value	Mean Value	Min Value	Max Value	Mean Value	Min Value	Max Value	Mean Value
5 × 5	174,410	4.36	0	360	178.22	0	78.21	7.37	−0.7	44.38	0.39	1	5	2.93
10 × 10	74,521	7.45	0	259.99	181.532	0	78.25	6.94	−0.601	36.76	0.52	1	5	2.92
25 × 25	28,875	18.05	0	359.38	180.63	0	70.31	6.73	−0.9	55.03	1.27	1	5	2.89
50 × 50	13,940	34.85	0	253.19	180.05	0	26.35	4.37	−0.92	66.67	2.29	1	5	2.86
100 × 100	6659	66.59	0	351.36	179	0	44.9	5.65	−1.28	98.02	4.14	1	5	2.83
200 × 200	3115	124.6	0	347.14	178.2	0	34.27	5.09	−0.93	114.71	6.95	1	5	2.81
500 × 500	1079	269.75	0	333.61	178.61	0	26.35	4.37	−1.18	145	13.15	1	5	2.77
1000 × 1000	445	445	0	277.778	176.653	0	23.2	4.17	−0.00023	227.476	21.51	2	5	2.77

3.2.2. Coastal Slope Example

The slope is defined as the ratio of “rise” (height) to “run” (distance). This paper focuses on a narrow coastal belt near the shoreline. A longer “run” along the western Istrian coast indicates higher vulnerability ranks as it corresponds to low steepness due to insignificant “rise” (Figure 2). Almost all cell dimensions exhibit an upward trend of higher vulnerability rank share with an increase in cell dimensions. An upward trend was not shown for the 5 × 5 m and 10 × 10 m cell dimensions, which display more diverse vulnerability rankings (Figure 8). Cell dimension change is inversely proportional to maximum and mean slope values (Table 5). The upward trend of higher-rank vulnerability with increasing cell size, observed in most cases, suggests that larger cells tend to generalise slope characteristics, potentially underrepresenting critical zones of low steepness that are highly susceptible to erosion and flooding. Therefore, using 5 × 5 m cell dimensions for analysing coastal data preserves localised slope variability. The methodological framework is better positioned to support vulnerability assessments in similar coastal settings by capturing these detailed differences.

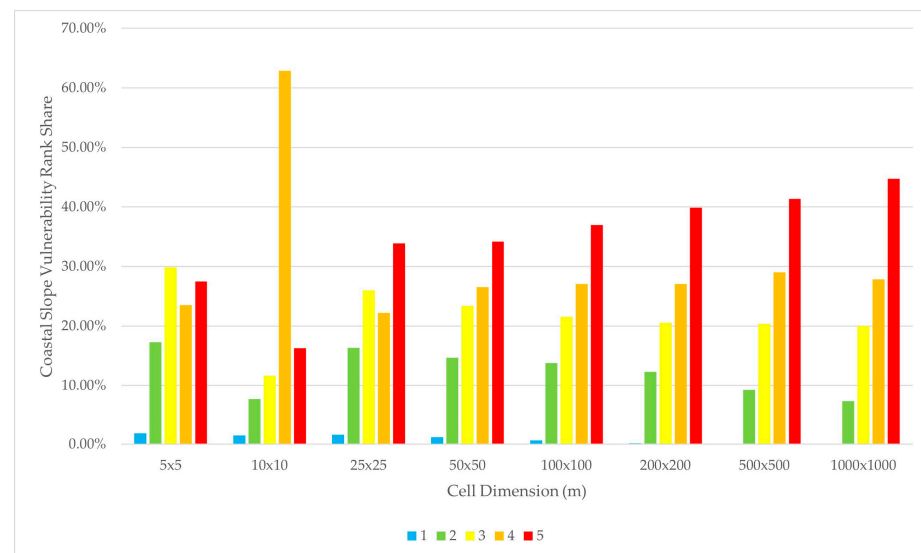


Figure 8. Coastal slope vulnerability rank share by different cell dimensions.

3.2.3. Coastal Height Example

Considering coastal height, low vulnerability ranks exhibit an upward trend with an increase in cell dimension, while high vulnerability ranks show the opposite trend (Figure 9). Such trends and vulnerability rankings are expected since larger cells reach further inland and include higher altitudes in the calculation. The increase in cell dimensions increases the maximum and mean height values (Table 5). Smaller cell dimensions (e.g., 5×5 m) effectively capture the variability in coastal height, particularly in low-lying areas most vulnerable to sea-level rise and flooding. Small natural beaches are a key attraction for tourists in Istria, and smaller-dimension cells enable a more precise analysis of their vulnerability. As cell dimension increases, higher vulnerability ranks decline, and lower vulnerability ranks become more prominent, reflecting the averaging effect of larger grids, which incorporate inland areas with greater elevations. This trend demonstrates the importance of fine-resolution grids in accurately assessing vulnerability, particularly in regions where elevation is crucial. Such results directly support this paper's aim to determine optimal cell dimensions for precise coastal vulnerability analysis, ensuring that critical low-lying zones are not underestimated in the assessment process.

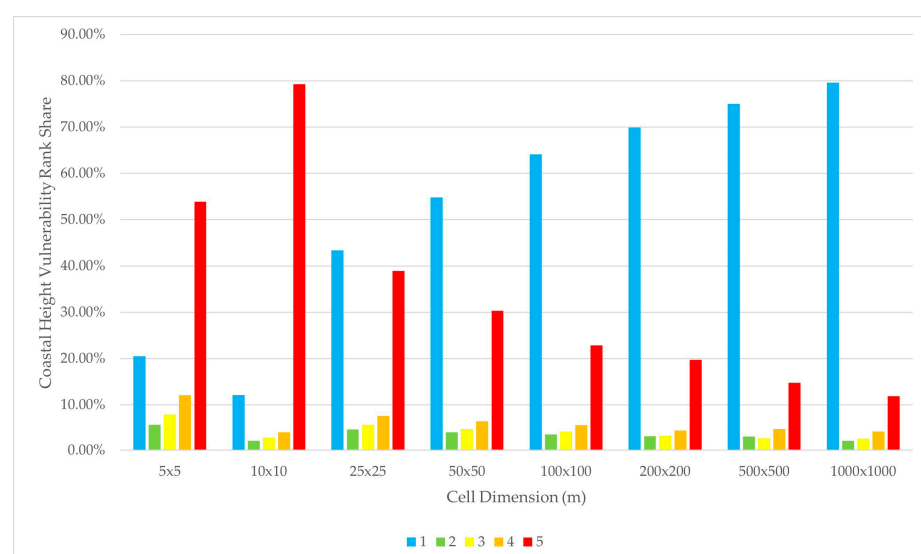


Figure 9. Coastal height vulnerability rank share by different cell dimensions.

3.2.4. Coastal Type Example

The share of vulnerability ranks (Figure 10) does not differ significantly with a change in cell dimensions, although larger dimensions do not possess vulnerability rank 1—high rocky coast ($>40^\circ$). Cell dimension change is inversely proportional to mean coastal type vulnerability values (Table 5). Coastal type vulnerability ranks remain consistent across different cell dimensions, although smaller cells (e.g., 5×5 m) provide a more detailed representation of localised variations (Figure 5). Larger cells tend to generalise the coastal type, potentially masking smaller but critical areas of high vulnerability, such as anthropogenically modified coasts or fine-grained sediment zones. This consistency across scales supports the robustness of the classification but also emphasises the importance of smaller grids for accurately identifying subtle yet significant differences.

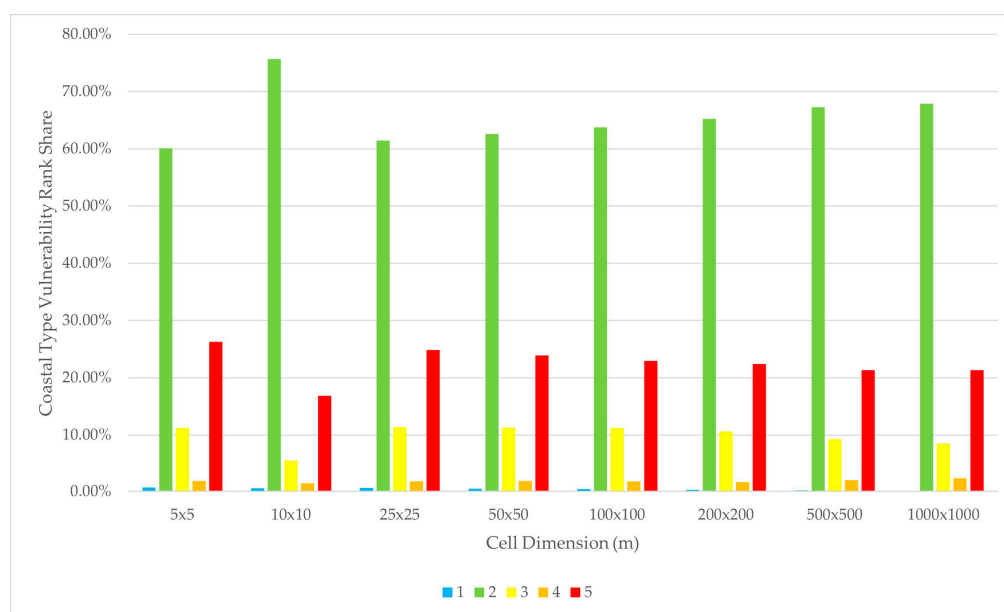


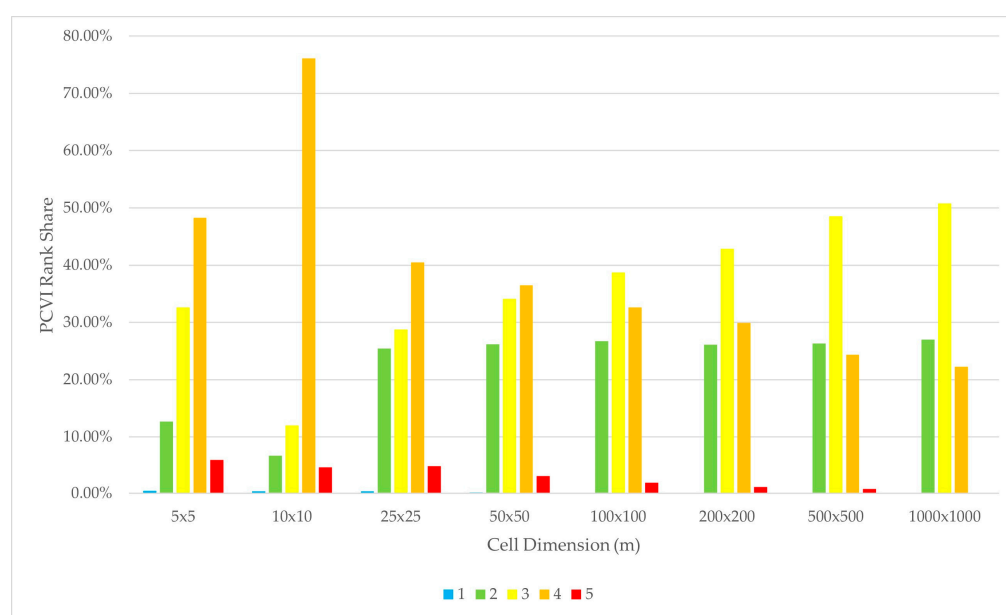
Figure 10. Coastal type vulnerability rank share by different cell dimensions.

3.2.5. PCVI Example

A crucial aspect of coastal vulnerability assessment is accurately capturing spatial variability. The choice of cell dimensions plays a pivotal role in this process, influencing the analysis's granularity and identifying high-risk areas. Smaller cell dimensions result in a more granular and diverse representation of vulnerability ranks, effectively preserving the heterogeneity of coastal features. In contrast, larger cell dimensions lead to data homogenisation, averaging out variability and masking outlier ranks that highlight critical risk areas (Table 6). Smaller cell dimensions provide a more detailed and diverse representation of vulnerability ranks, preserving the heterogeneity of coastal features. Furthermore, cell dimension increase decreases the predominant vulnerability rank and the mean PCVI value (Table 4). These results underscore the necessity of employing finer cell resolutions to represent localised differences effectively and ensure a more accurate assessment of coastal vulnerability (Figure 11).

Table 6. Statistics on the Physical Coastal Vulnerability Index by different cell dimensions (light orange: predominant vulnerability rank).

Cell Size (m)	PCVI					Total Share	Mean (Vulnerability Rank)
	1	2	3	4	5		
	Share	Share	Share	Share	Share		
5 × 5	0.44%	12.68%	32.62%	48.30%	5.97%	100.00%	3.47
10 × 10	0.40%	6.75%	12.01%	76.12%	4.73%	100.00%	3.78
25 × 25	0.37%	25.46%	28.79%	40.51%	4.88%	100.00%	3.24
50 × 50	0.18%	26.18%	34.10%	36.50%	3.04%	100.00%	3.16
100 × 100	0.11%	26.70%	38.74%	32.62%	1.83%	100.00%	3.09
200 × 200	0.03%	26.10%	42.86%	29.92%	1.09%	100.00%	3.06
500 × 500	0.00%	26.32%	48.56%	24.37%	0.74%	100.00%	3.00
1000 × 1000	0.00%	26.97%	50.79%	22.25%	0.00%	100.00%	2.95

**Figure 11.** PCVI rank share by different cell dimensions.

3.3. Physical Coastal Vulnerability Index

The analysis shows that the most appropriate method is M3. Implementation of the M3 PCVI calculation method resulted in the vulnerability rank distribution shown in Table 5. Almost half of the Istrian coast (48.30%) is highly vulnerable, with 80.92% falling between moderate and high vulnerable ranks (Table 7). The average vulnerability rank for the entire Istrian peninsula is 3.47, with an average of 3.59 for western municipalities and 3.25 for eastern municipalities.

Table 7. PCVI (cell number by vulnerability rank).

Cell Size (m)	1	2	3	4	5	Total	Total Share
5 × 5	761	22,120	56,888	84,232	10,409	174,410	
	0.44%	12.68%	32.62%	48.30%	5.97%		100.00%

The predominant rank was high vulnerability, exhibited by seventeen municipalities, while six exhibited moderate and one low vulnerability (Table 8). Kršan municipality had the highest share of ranks one and two, Buje Buie municipality predominantly exhibited rank three, Vodnjan–Dignano municipality predominantly exhibited rank four,

and Brtonigla–Verteneglio municipality predominantly exhibited rank five, with 27.74% (Figure 12). The ranking shown in Table 8 reflects the results in Table 7.

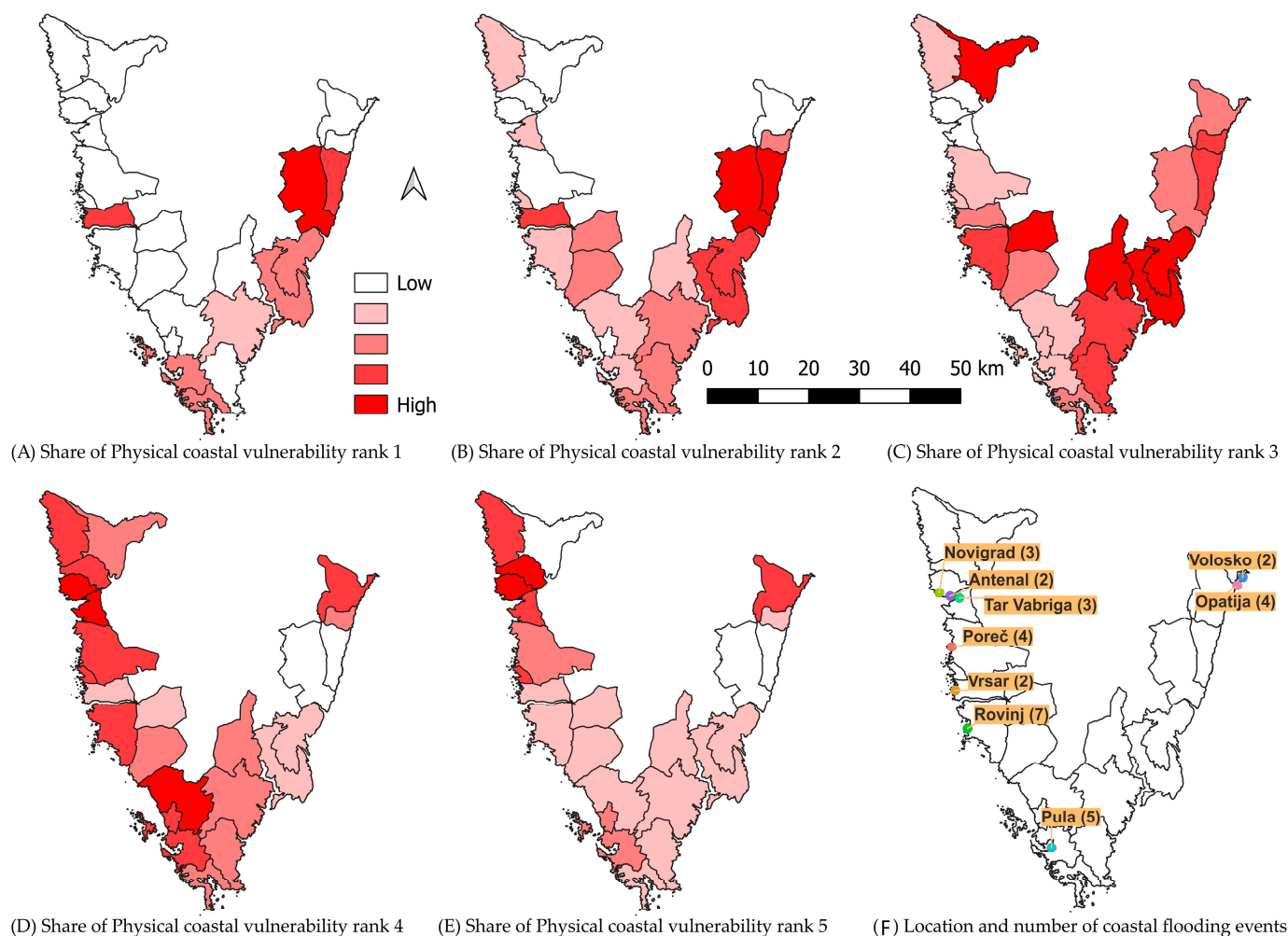


Figure 12. Municipality physical coastal vulnerability cell share by vulnerability rank (A–E); Flooding events along the Istrian coast (F) [48].

Table 8. Share of vulnerability rank by municipalities (light orange shading: maximum value by municipalities, bold: maximum value by rank).

Municipality	Coast (East—E, West—W)	1	2	3	4	5
Bale–Valle	W	0.00%	13.70%	35.27%	49.58%	1.45%
Barban	E	0.00%	5.96%	50.10%	42.40%	1.54%
Brtonigla–Verteneglio	W	0.00%	1.17%	9.14%	61.96%	27.74%
Buje–Buie	W	0.00%	1.78%	57.67%	39.89%	0.67%
Fažana–Fasana	W	0.00%	3.95%	25.31%	61.57%	9.17%
Funtana–Fontane	W	0.00%	6.02%	26.62%	52.24%	15.12%
Kanfana	W	0.00%	13.91%	54.44%	30.77%	0.89%
Kršan	E	4.34%	42.08%	34.27%	18.57%	0.73%
Labin	E	0.24%	22.26%	45.94%	30.59%	0.96%
Ližnjan–Lisignano	E	0.02%	11.62%	37.64%	49.62%	1.10%
Lovran	E	0.00%	14.66%	40.60%	42.92%	1.83%

Table 8. *Cont.*

Municipality	Coast (East—E, West—W)	1	2	3	4	5
Marčana	E	0.14%	17.86%	39.28%	41.50%	1.23%
Medulin	W	0.50%	14.42%	33.72%	47.89%	3.47%
Mošćenička Draga	E	3.73%	35.66%	40.75%	19.58%	0.28%
Novigrad-Cittanova	W	0.00%	1.17%	9.11%	62.08%	27.65%
Opatija	E	0.00%	1.77%	29.01%	57.25%	11.97%
Poreč-Parenzo	W	0.00%	3.80%	25.60%	60.45%	10.15%
Pula-Pola	W	0.21%	8.52%	27.81%	55.72%	7.75%
Raša	E	0.37%	21.81%	44.24%	32.67%	0.91%
Rovinj-Rovigno	W	0.03%	7.22%	36.53%	51.46%	4.75%
Tar-Vabriga-Torre-Abrega	W	0.00%	5.18%	15.71%	62.63%	16.48%
Umag-Umago	W	0.00%	7.62%	27.11%	52.15%	13.11%
Vodnjan-Dignano	W	0.00%	4.53%	23.03%	71.56%	0.88%
Vrsar-Orsera	W	2.21%	25.39%	31.61%	38.51%	2.27%

Due to the small cell dimension and restriction on printing maps, the physical vulnerability is shown on a municipality level. Rather than generalise calculated physical coastal vulnerability on a municipality level, vulnerability is presented as a cell share of five vulnerability ranks per each Istrian coastal municipality (Figure 12). The municipalities with a higher cell share of higher, more vulnerable ranks are located along the western Istrian coast, while municipalities with a higher cell share of lower, less vulnerable ranks are located along the eastern Istrian coast (Figure 12).

3.4. Assessment of Results and Implications

The calculation of the PCVI involves determining a central or typical value for the vulnerability rank based on the input values from each variable. However, using the central value can be misleading, as it may obscure outliers and high vulnerability values, which are crucial for disaster risk managers. Most current calculation methods can be categorised into two main groups: the mean (or modified mean) calculation methods [9,22,45,46], and geometric mean (or modified geometric mean) methods [7,8,49]. These two groups can be further divided based on how they incorporate weighted values. Weighted values can be assigned to each variable based on their importance, determined by the author or the scope of the research, or just for selected ones [8,45,50,51]. Using self-weighted values prioritises high vulnerabilities. We believe that our modification, which implements self-weights and is described as the M3 method, successfully addresses this issue.

Flood records from Istria [48,52] suggest that the results obtained using the M3 method align well with documented coastal flooding events. Municipalities with higher shares of Rank 4 and 5 vulnerabilities in the PCVI model, such as Brtonigla–Verteneglio, Novigrad, Fažana, Rovinj, and Poreč (Figure 12), have a well-documented history of coastal flooding [48,52], supporting the reliability of the proposed PCVI model.

For instance, in the city of Rovinj, five flood events were recorded between 1966 and 2007, whereas seven occurred between 2008 and 2023. This corresponds to an increase in flood frequency from 0.119 events per year (1966–2007) to 0.437 events per year (2008–2023), reducing the return period from 8.4 years to 2.3 years (Lončar & Vujičić, 2025, in preparation). The rising frequency of flooding, likely driven by increased exposure to Adriatic seiches and storm surges [16], indicates a growing vulnerability of these cities to coastal flooding.

Evaluating the PCVI of the Istria peninsula using the M3 method revealed that municipalities along the western Istrian coast are more vulnerable (Figure 12). This finding is consistent with the observable differences in coastal morphometric characteristics, as shown Figure 2. The increased vulnerability of the western coast aligns with the greater frequency of flood events recorded in that area compared to the eastern Istrian coast [48].

While the M3 method presents a more refined approach to coastal vulnerability assessment, further empirical validation with field data, remote sensing, and hydrodynamic modelling is necessary to confirm its robustness. Future research should apply this methodology to other coastal regions—particularly those with complex geomorphological characteristics—to assess its broader applicability and improve coastal risk mitigation strategies.

Previous studies on coastal vulnerability assessment have primarily relied on established methodologies, such as the arithmetic mean (M1), geometric mean (M2), and their modified versions [33,45,46]. These methods are widely used due to their simplicity and ability to integrate multiple variables into a single vulnerability index. However, a limitation of these approaches is their tendency to average out vulnerability values, which can mask extreme high-risk areas [7,22].

In contrast, this study introduces an alternative calculation method—the second root of the self-weighted arithmetic mean (M3)—which has not been previously applied in coastal vulnerability assessments. The M3 method prioritises higher vulnerability values, making it more effective in identifying areas of critical risk. Traditional central tendency measures, such as the arithmetic mean, often create a Gaussian distribution, resulting in the dilution of vulnerability extremes [29]. By applying a self-weighting mechanism, M3 ensures that regions with inherently higher vulnerability are more accurately represented. This is particularly relevant for highly heterogeneous coastal environments, such as the karstic coastline of the Istrian Peninsula, where standard methods may fail to capture small-scale variations in coastal morphology and exposure to climate hazards.

Another advantage of M3 is that it avoids oversimplification. Many existing studies aim to create balanced vulnerability indices that account for all factors equally, but this approach can obscure critical high-risk zones [7,8]. By assigning greater emphasis to higher vulnerability variables, M3 ensures that at-risk coastal areas receive the necessary prioritisation in vulnerability assessments. This aligns with recent calls in climate adaptation research for more precise, high-resolution risk assessments, particularly in small-scale coastal environments with high urbanisation pressures [53] such as the Istrian peninsula.

4. Conclusions

The methodology in this paper involves testing multiple formulas to identify the most accurate analysis of coastal vulnerability. The findings suggest that smaller cell dimensions (5×5 m) are most appropriate in capturing significant physical characteristics of the coastline, resulting in more targeted and effective vulnerability assessments.

Given the limitations of traditional arithmetic and geometric means in emphasising high-risk areas, this study introduces the M3 method, which applies a self-weighted mechanism to prioritise extreme vulnerability values. This approach allows for a more refined differentiation of at-risk coastal zones.

The chosen calculation method, the second root of the self-weighted arithmetic mean (M3), emphasises variables that indicate higher vulnerability, aiming to avoid the pitfalls of overly generalised data that can obscure critical at-risk areas. The validation of the M3 method against historical flood records patterns reinforces its effectiveness in identifying high-risk coastal areas. Unlike traditional central tendency measures, M3 prioritises extreme vulnerabilities, making it a more suitable tool for localised coastal risk assessments.

While the M3 and M4 methods effectively highlight high vulnerability values and capture spatial variability, validation with independent data is necessary to confirm their robustness. Future studies should incorporate field measurements or compare results with outputs from other established vulnerability indices, such as those applied to similar Mediterranean regions. Additionally, sensitivity analysis could assess the impact of weighting factors in the M3 and M4 methods on the final vulnerability rankings. Such validation would improve the reliability and applicability of the methodology for broader use.

Although the manual classification of coastal types allowed for detailed interpretation, future methodology applications could benefit from integrating automated approaches, such as supervised classification algorithms, to reduce subjectivity and improve scalability.

This paper illustrates the role of high-resolution grids in precisely identifying vulnerable areas and offers a methodological framework that can be adapted for coastal regions worldwide. A comprehensive physical assessment lays the groundwork for integrating socio-economic and policy considerations, contributing to improved climate resilience and targeted adaptation strategies in vulnerable coastal zones.

To enhance the applicability of the PCVI methodology, future research should focus on cross-validation with empirical data and refine the weighting mechanisms for individual physical variables. Expanding the methodology to include socio-economic factors would provide a more holistic vulnerability assessment framework, combining physical and societal vulnerabilities to offer more comprehensive guidance for climate adaptation and coastal zone management.

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