January 2026

Fondazione Eni Enrico Mattei

Working Paper

04.2026

Global spatiotemporal multi-criteria analysis of coastal risk: current and future hot spots and clusters

Marco Bidoia, Carlo Giupponi

Global spatiotemporal multi-criteria analysis of coastal risk: current and future hot spots and clusters

Marco Bidoia (Department of Economics, Ca' Foscari University of Venice and Fondazione Eni Enrico Mattei), **Carlo Giupponi** (Department of Economics, Ca' Foscari University of Venice and Fondazione Eni Enrico Mattei)

Summary

Coastal zones are among the environments most threatened by climate change. Although various efforts for global mapping and classification of coastal social and ecological systems have been undertaken, the ability to analyse and describe the spatial heterogeneity and multidimensionality of these phenomena remains limited. In the current study, we developed a methodological framework for assessing risk from extreme sea levels and examined its application at the global level. A multi-criteria analysis method was applied to the current scenario and to two future combinations of shared socioeconomic (SSP2 and 5) and representative concentration pathways (RCP4.5 and 8.5), accounting for risk attitudes. Risk maps derived from multi-criteria analysis aggregation of spatial indicators of hazard, vulnerability, and exposure enabled the identification of global hot spots, comprising large areas facing high levels of risk, mostly located in Northern Europe, South-East Asia and Southern USA. Spatial clusters with common risk features were identified and mapped using multivariate analysis. The results contribute to improving the state of the art by providing a synoptic view of global coastal risks. Given the high spatial resolution (1 km), the proposed methods may also be helpful for improving adaptation strategies at the regional and national scales and for facilitating the sharing of solutions between areas with similar situations identified by cluster mapping.

Keywords: Coastal zones, climate change, extreme sea levels, scenario, multi-criteria analysis, data-driven analysis, adaptation

JEL Classification: Q5

Corresponding Author
Marco Bidoia
Department of Economics, Ca' Foscari University of Venice
San Giobbe, Cannaregio 873 - 30121 Venice
marco.bidoia@unive.it

Global spatiotemporal multi-criteria analysis of coastal risk: current and future hot spots and clusters

Marco Bidoia[1,2*], Carlo Giupponi[1,2]

Abstract

Coastal zones are among the environments most threatened by climate change. Although various efforts for global mapping and classification of coastal social and ecological systems have been undertaken, the ability to analyse and describe the spatial heterogeneity and multidimensionality of these phenomena remains limited. In the current study, we developed a methodological framework for assessing risk from extreme sea levels and examined its application at the global level. A multi-criteria analysis method was applied to the current scenario and to two future combinations of shared socioeconomic (SSP2 and 5) and representative concentration pathways (RCP4.5 and 8.5), accounting for risk attitudes. Risk maps derived from multi-criteria analysis aggregation of spatial indicators of hazard, vulnerability, and exposure enabled the identification of global hot spots, comprising large areas facing high levels of risk, mostly located in Northern Europe, South-East Asia and Southern USA. Spatial clusters with common risk features were identified and mapped using multivariate analysis. The results contribute to improving the state of the art by providing a synoptic view of global coastal risks. Given the high spatial resolution (1 km), the proposed methods may also be helpful for improving adaptation strategies at the regional and national scales and for facilitating the sharing of solutions between areas with similar situations identified by cluster mapping.

Keywords

Coastal zones, climate change, extreme sea levels, scenario, multi-criteria analysis, data-driven analysis, adaptation

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC, 2019) classifies coastal zones as high-risk areas, with flooding becoming an increasingly frequent and severe threat. A substantial amount of research has been dedicated to quantifying these phenomena. A study by Vafeidis et al. (2008) and more recent research by Athanasiou et al. (2024) have contributed by expanding data collection on coastal risk-related variables, typically by segmenting the coastline into discrete segments for analysis. However, those segments are rather large and are not employed to create a comprehensive risk index. Studies by Hinkel et al. (2014) and Tiggeloven et al. (2020) explored adaptation costs, which are crucial for understanding the financial implications of climate change. Other studies, such as those conducted by Scussolini et al. (2016), Tiggeloven et al. (2020), and Haasnoot et al. (2021), developed or applied a global flood protection layer based on estimated relationships between the extent of flood defences, exposure, and economic development.

[1] Department of Economics, Ca' Foscari University of Venice
[2] Fondazione Eni Enrico Mattei, Venice
[*] Correspondence: marco.bidoia@unive.it

Furthermore, recent studies have developed various proposals regarding spatial indicators, such as expected annual damage and the population exposed to flooding (Hinkel et al., 2014, Tiggeloven et al., 2020, Haasnoot et al., 2021, Kirezci et al., 2023, Kirezci et al., 2025). Although these studies are valuable for assessing various dimensions of risk, they tend to narrow the scope of global assessment, overlooking some risk factors (e.g. socioeconomic conditions). Thus, a truly holistic approach encompassing the main dimensions of risk is still lacking. To address the limitations of existing methods in the field, Rocha et al. (2023) called for the urgent adoption of a generalisable framework to derive coastal risk indices and to consider more socioeconomic variables, thus requiring methodologically sound approaches for dealing with multiple dimensions and their aggregation. However, most methods proposed so far provide very simplistic solutions, such as weighted sums. Only in some studies, multi-criteria analysis (MCA) techniques have been combined with data-driven methods (Giupponi et al., 2015, Tanim et al., 2022).

Following recent developments in datasets and analyses with high spatial and temporal resolutions and in the literature on coastal risk, drawing from IPCC reports (IPCC, 2019, IPCC, 2023) and other sources (Satta et al., 2017, Wolff et al., 2018, UNEP, 2021, Rocha et al., 2023), this work explored new avenues for providing a comprehensive but concise global risk index. We went beyond the state of the art by proposing a methodological framework for the assessment of global coastal risks arising from extreme sea levels (ESL) at 1 km spatial resolution. We developed a multidimensional approach to provide a comprehensive assessment of risk under current conditions (baseline) and in the future using two different combinations of shared socioeconomic pathways (SSP) and representative concentration pathways (RCP), with a novel approach to deal with uncertainty deriving from different risk attitudes.

Uncertainty attitude in coastal risk assessment has received limited consideration in recent literature. Decision-making under deep uncertainty has been extensively studied in other fields related to global change (Lempert, 2019), highlighting the importance of incorporating different attitudes when evaluating long-term climate-related risks. Although traditional methods typically assume a fixed view of risk, variability in stakeholders' attitudes is crucial for accurately assessing impacts (Savage, 1954, Gul and Pesendorfer, 2014). We addressed this issue by incorporating varying risk attitudes in scenario analysis, through the adoption of the weighted ordered weighted averaging (WOWA) method (Torra, 1997).

Furthermore, to fully exploit the informative content of the multidimensional dataset, statistical analyses can be applied to the datasets. For example, Athanasiou et al. (2024) applied clustering techniques to identify areas with common values of physical variables. We extended this approach by applying Principal Component Analysis (PCA) followed by k-means clustering to socioeconomic, environmental, and cultural variables and the final index, thus allowing for the identification of spatio-temporal risk patterns occurring across the globe.

2. Methods

2.1 Risk assessment framework and spatial indicators

According to the IPCC (2012), risk can be considered as the combination of exposure (E), vulnerability (V), and hazard (H) variables; here, risk was calculated as the product of these factors, as proposed by UNEP (2002):

$$R = H \times E \times V \qquad \text{(Equation 1)}$$

In turn H, E, and V can be defined according to spatial indicators selected following the indication of the current literature and based on the availability of reliable spatial data and future projections.

Concerning the uncertainty about future developments, a baseline scenario was defined by mapping the most recent values of the variables and representing the very optimistic view that things will not change until the end of the century. Two future scenarios were developed to describe what may happen during the last 20 years of the 21st century, analysing plausible long-term risk scenarios with an increasing level of pessimism (RCP4.5

combined with SSP2 and RCP8.5 combined with SSP5). Low Elevation Coastal Zones (McGranahan et al., 2007) and all areas within a 10 km buffer from the coastline (JRC, 2011) were included in the analysis.

To account for hazard, 1:100 years ESL layer was employed, because of its ability to represent and summarise the most relevant impact of climate change on coastal zones (Kirezci et al., 2023, Hinkel et al., 2014).

For exposure, four indicators were selected: (i) population count (IPCC, 2012), (ii) urban area coverage (%) (IPCC, 2012), agricultural land cover (%) (IPCC, 2019), and (iv) presence of UNESCO heritage sites, according to the IPCC (2023) and as confirmed for the Mediterranean by Reimann et al. (2018).

Five physical, ecological, and socioeconomic spatial indicators were aggregated to assess vulnerability: (i) distance from rivers to take into account compounded flooding episodes (IPCC, 2019, Khanal et al., 2019); (ii) coastal ecosystems that contribute to morphological stability and mitigate hazards (tidal wetlands, coral reefs, and seagrasses) (IPCC, 2019); (iii) coastal erosion, which, as highlighted by Wolff et al. (2018) and Rocha et al. (2023), can modulate the impacts of rising sea levels; (iv) gross domestic product (GDP) per capita, given that the availability of economic resources is one of the main drivers limiting vulnerability and providing opportunity for adaptation (IPCC, 2023); and (v) economic inequality (Gini index) (Farris, 2010) at the national scale, which increases societal vulnerability (IPCC, 2023) and lowers community resilience; furthermore, uneven distribution of wealth can fuel social conflicts (IPCC, 2019).

Technical details and information on the selected datasets are reported in the Supplementary Materials.

2.2 Aggregation and clustering methods

Aggregation was performed using WOWA (Torra, 1997), which enables consideration of the relative importance of the variables using weights (provided by nine experts interviewed at an interdisciplinary workshop on sea-level rise), as well as a stylised description of risk attitudes. Compared with ordered weighted averaging (OWA), WOWA produces more robust results when accounting for both criterion importance and ordinal weights (Torra, 1997). Although OWA has previously been employed in climate change risk assessments (Fullér, 1996, Giupponi et al., 2015, Cian et al., 2021, Zhang et al., 2021), WOWA has not previously been used in this context.

Details on the computation of the final risk index and on the quantification of the associated uncertainty are available in the supplementary materials.

For the identification of spatial and temporal patterns, the use of PCA followed by clustering is an established methodology in the climate change and environmental economics literature (Addy et al., 2021, Alaniz et al., 2022, Díaz González et al., 2022). Here, PCA was applied to a dataset that included the ensemble of all spatial indicators (H, E, and V under the three scenarios) to reduce redundancy in the data by retaining the three Principal Components (PCs). Finally, cluster analysis was applied to the PCA results (nine variables constructed from the combination of three PCs and three scenarios) with the k-means algorithm.

3. Results

3.1 Spatiotemporal global risks

The global risk hotspots under different scenarios are shown in Figure 1: dramatic changes are expected in the future, with an expansion of high-risk areas compared with the baseline scenario. Although risk index values can range from 0 to 1 in theory, none of the output values exceeded 0.65.

Even under a neutral scenario, the extent of regions threatened by ESL events increased significantly, while the pessimistic scenario further amplified the intensity of risk. The population living in extreme-risk areas (99th quantile) was estimated to be approximately 50,000, 6 million, and 60 million people under the optimistic, neutral, and pessimistic scenarios, respectively.

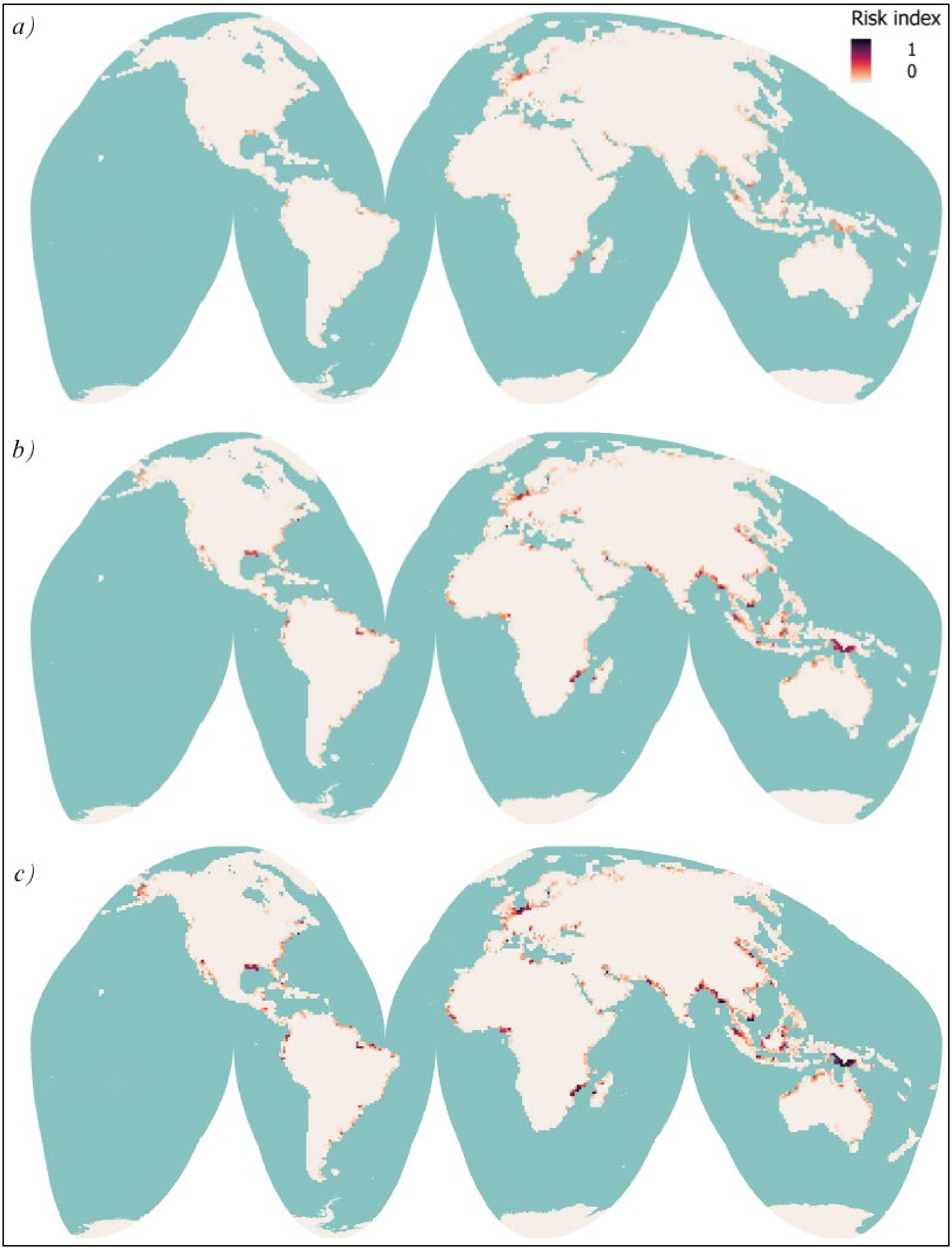

__Fig. 1: Global risk.__ Panels a), b), and c) represent optimistic, neutral, and pessimistic scenarios, respectively. In the maps, risk values were normalised to 1 to facilitate visual interpretation of results.

At baseline, high-risk hotspots are already evident in northern Europe, particularly along the North Sea coasts, as well as in parts of Asia, including regions around the Bay of Bengal and eastern China. In the neutral scenario, the spatial extent of risk increased considerably, particularly affecting north-western and southern Europe, the Mediterranean basin, and large portions of Southern Asia. In Africa, an expansion of at-risk areas was observed, particularly in West Africa and parts of the Nile Delta. In the Americas, high-risk zones that were initially limited to localised areas in the baseline scenario became more widespread, affecting the eastern seaboard of the United States (US), the Gulf of Mexico, and sections of the Caribbean and South American Atlantic coasts.

High-risk areas were not always found along the immediate coastline: in some regions, the exposure and vulnerability near the shoreline are relatively low, while further inland, in low-elevation zones with a high concentration of assets and population, the risk levels become considerably higher. This pattern is evident in parts of Europe, South and East Asia, and the Americas, where major urban centres situated slightly inland showed elevated risk. The trends observed at the country level (data available in the Excel file of the supplementary materials) supported the patterns observed in Figure 1; countries such as the Netherlands, Bangladesh, Vietnam, China, Nigeria, the US, and Brazil, which appeared as areas of high or growing risk in the maps, also showed some of the highest increases in mean risk index values. In addition, several Small Island Developing States (SIDS), especially in the Caribbean and the Indian Ocean, stood out as having particularly high national risk values, despite not being easily identifiable in the global maps. The table also shows that, in Asia, countries like Bangladesh, Vietnam, and China consistently dominate the upper end of the risk distribution across scenarios, while in Africa, the rise in risk is most prominent in the north-western Atlantic coast and in the south-eastern Indian Ocean. In the Americas, results show growing risk along the south-western US, Mexico, Colombia, and Brazil Atlantic coasts.

3.2 Principal component analysis and clustering

The first three PCs of the examined data were considered for cluster analysis according to the Kaiser-Guttman rule (Kaiser, 1960). Combined, these PCs retained 86% of the total variance in the original dataset. A first result of this analysis is that risk patterns remained stable in the scenarios because the three sub-indices had the same sign and comparable values of correlations with the three PCs under all scenarios. The component loadings indicated that the first PC was strongly positively correlated with vulnerability, the second was strongly positively correlated with exposure, and the third was strongly negatively correlated with hazard.

The squared sum of distances was computed by letting the number of clusters vary from 2 to 15. The most consistent and interpretable results, also according to the Elbow method (Ketchen and Shook, 1996), were obtained with four clusters, both in terms of the spatial distribution and of the meaningfulness of clusters (Table 1).

Table 1: Clustering results. Average values of PCs, H, E, and V sub-indices and of the risk index

Clust	PC 1	PC 2	PC 3	Vul. Opt.	Exp. Opt.	Haz. Opt.	Vul. Neu.	Exp. Neu	Haz. Neu.	Vul. Pes.	Exp. Pes.	Haz. Pes.	Risk Opt.	Risk Neut.	Risk Pes.
0	0.74	0.51	–0.86	0.53	0.30	0.76	0.60	0.54	0.86	0.67	0.68	0.87	0.12	0.28	0.40
1	1.36	0.33	2.36	0.52	0.31	0.01	0.59	0.53	0.41	0.67	0.66	0.73	0.00	0.14	0.33
2	–0.79	–2.29	–0.12	0.49	0.08	0.67	0.57	0.21	0.82	0.65	0.29	0.84	0.03	0.10	0.16
3	–2.97	1.41	0.39	0.25	0.22	0.68	0.34	0.48	0.82	0.38	0.62	0.85	0.04	0.14	0.20

Clust. – Cluster number; PC 1–3 – Principal Components 1 to 3; Vul. – Vulnerability; Exp. – Exposure; Haz. – Hazard; Opt. – Optimistic scenario; Neu. – Neutral scenario; Pes. – Pessimistic scenario.

Below, the main features of the clusters are discussed separately, with clusters ordered by increasing total surface area (Table 2). Cluster 0, identified as “High coastal risks”, is characterised by the highest average values for hazard and vulnerability, while exposure is similar to Cluster 1. These regions are already at high risk under optimistic scenario, and the average risk is the highest also in future scenarios. The correlation with the PCs for this cluster exhibited a strong positive value for PC1 (vulnerability), a moderate positive value for PC2 (exposure), and a negative value for PC3 (hazard). Cluster 1, “Increasing hazards: a future at risk”, consists of areas with the lowest baseline risk because current hazard values are negligible. The main feature of this cluster is the ramping values of hazard in future scenarios, indicating significantly increasing risks, which ranked as the second-highest average value after Cluster 0 in the pessimistic scenario. The correlation with the PCs for Cluster 1 exhibited a positive value for PC1, a smaller positive value for PC2, and a slightly positive value for PC3. Cluster 2, “Low exposure: low risks”, is characterised by high hazard levels but low exposure and moderate vulnerability. Although these areas are not currently at high risk because of low exposure, hazard remains a significant factor. In the pessimistic scenario, as exposure and vulnerability increase, also the risk increase. The PCs for Cluster 2 showed a negative value for PC1, a strongly negative value for PC2, and a moderately negative value for PC3, reflecting the fact that hazard is the dominant factor in this cluster despite low exposure and vulnerability. This cluster exhibited the lowest average value of the risk index in future scenarios and maintained the most compact risk distribution across all cases. Cluster 3, “High hazard with low vulnerability: moderate risks” was characterised by high levels of exposure and hazard but low vulnerability. This results in an intermediate level of risk, driven by exposure and hazard, increasing as vulnerability increases in the pessimistic scenario. The PCs for Cluster 3 showed a highly negative value for PC1, a strong positive value for PC2, and a moderate positive value for PC3, indicating that exposure and hazard are the primary drivers of risk, with vulnerability becoming more significant only in the pessimistic scenario. Cluster 3 is the smallest cluster in terms of surface area.

Table 2: Cluster surface areas

Cluster	Surface (km^2)
High coastal risks	295,718
Increasing hazards: future at risk	131,918
Low exposure: low risks	100,730
High hazard with low vulnerability: moderate risks	84,190

Regarding the global distribution of clusters, areas in the “High coastal risks” category are vast and widely distributed globally. Despite being a minority cluster, areas in the “High hazard with low vulnerability: moderate risks” category are also distributed throughout all continents. The “Increasing hazards: future at risk” cluster is mostly present in tropical areas. The cluster exhibiting the most localised distribution is “Low Exposure: low risks” and it appears only along the Arctic coasts and in northern Australia. This finding is unsurprising because these areas present very low exposure because of being largely uninhabited. The Indian/Pacific coasts of Oceania and Southeastern Asia exhibit the greatest heterogeneity in the cluster distribution.

While the geographical trends are in line with the findings of the existing literature, the values of the aggregated risk index show some original patterns, due to the broader integration of environmental and socioeconomic variables and to the innovative aggregation algorithm. If comparing our results with previous studies, such as the ones from Haasnoot et al. (2021) Tiggeloven et al. (2020) and Kirezci et al. (2023) we find a relatively higher severity of risk in Papua New Guinea and Indonesia, especially in future scenarios and a comparatively lower magnitude of risk in the U.S. Inclusion of different variables depicting more in detail vulnerability and exposure may explain this difference: in the latter low exposure and/or vulnerability mitigate hazard (cluster 2 and 3 are well represented) while in the former the opposite is happening (cluster 1 is dominant). On top of that, the high resolution of final results help in identifying relatively small high risk hotspots which, in the previous studies are not always evident due to their lower spatial detail. Example of punctual hot spots not evident before are areas along the easter coast of Taiwan, the Carribean coast of Mexico, in the central section of Moroccan coast and in Kenya.

The following section focuses on three areas of greater interest, while details of clustering results (global maps, boxplots of risk index and a breakdown of the distribution per country), can be found in the supplementary materials.

3.*3* Regional hot spots

North Sea

The first area of interest emerging from the global maps as a hot spot of coastal risk encompasses the coastal regions of the North Sea, where a combination of medium to high exposure and vulnerability, alongside extremely high hazard conditions, led to very high-risk index values, even in the baseline scenario. Most of these areas fell within the "High coastal risk" category. The relatively homogeneous risk distribution suggested that the region's risk index increases uniformly across scenarios while hazard levels remain stable. Risk in this area is primarily driven by high vulnerability and exposure. However, because this study adopted a global perspective with the aim of comparing the magnitude of risk across continents, local-scale analyses incorporating specific flood defence measures such as the extensive protections historically implemented in the Netherlands could refine estimates of current risks.

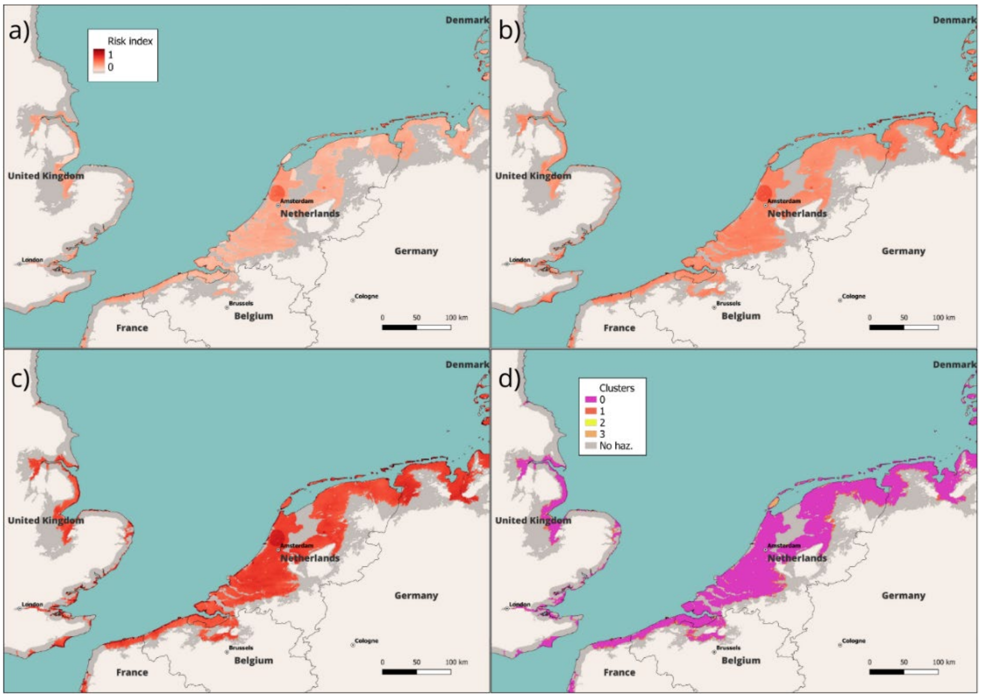

Fig. 2: North Sea. *Panels a), b), c), and d) represent optimistic, neutral, pessimistic scenarios and clustering results, respectively.*

Gulf of Bengal

The results suggest that the Bengal region is expected to experience a significant increase in risk under future scenarios, exacerbating the already considerable levels seen at baseline. High exposure levels contributed to inland areas sometimes being classified as riskier than coastal zones. The clustering results showed heterogeneous risk drivers, with "High coastal risk" and "High hazard with low vulnerability: moderate risks" being the most prevalent risk category, but with all categories represented. This finding suggests a complex interplay of risk drivers, where "High hazard with low vulnerability: moderate risks" highlighted locations where exposure and hazard are the dominant factors, while the "High coastal risk" category indicates regions already at severe risk. Additionally, "Increasing hazards: future at risk" is present in areas that could face rising hazard as a primary driver of future risk. Given the peculiar nature of this deltaic region, further local studies will benefit of these results for identifying effective adaptation strategies.

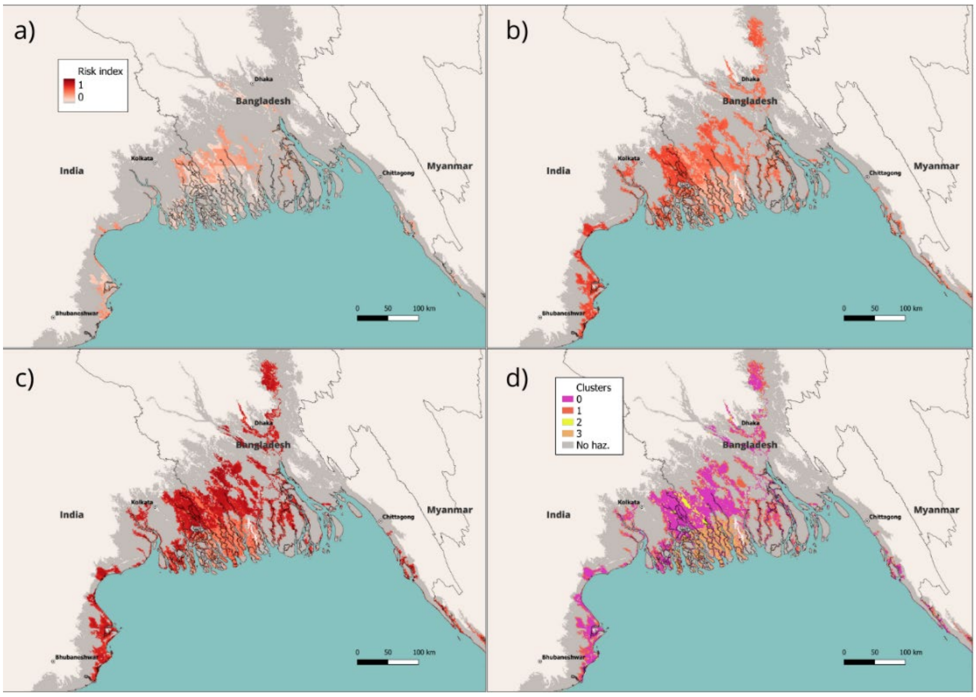

Fig. 3: Bangladesh. *Panels a), b), c), and d) represent optimistic, neutral, pessimistic scenarios and clustering results, respectively.*

Gulf of Mexico

Although risk patterns in the US states bordering the Gulf of Mexico exhibit similarities to Bangladesh in terms of increasing risk under future scenarios, particularly in the pessimistic projection, the underlying drivers differ. In these areas, "Low exposure: low risks" and "High hazard with low vulnerability: moderate risks" are well represented in addition to "High coastal risk." Unlike Bangladesh, where exposure plays a primary role, hazard is a stronger driver, particularly in areas classified as "Low Exposure: low risks", where low exposure and moderate vulnerability may still result in high hazard-driven risk. Meanwhile, "High hazard with low vulnerability: moderate risks" areas experience increasing risk because of their high exposure levels, a trend that become more pronounced in the pessimistic scenario. The presence of "High coastal risk" in inland areas highlights locations in which high vulnerability, exposure, and hazard coincide, leading to risk escalation. The combination of high hazard levels and growing exposure in the region suggests that this area requires very high investments to mitigate risk in future scenarios.

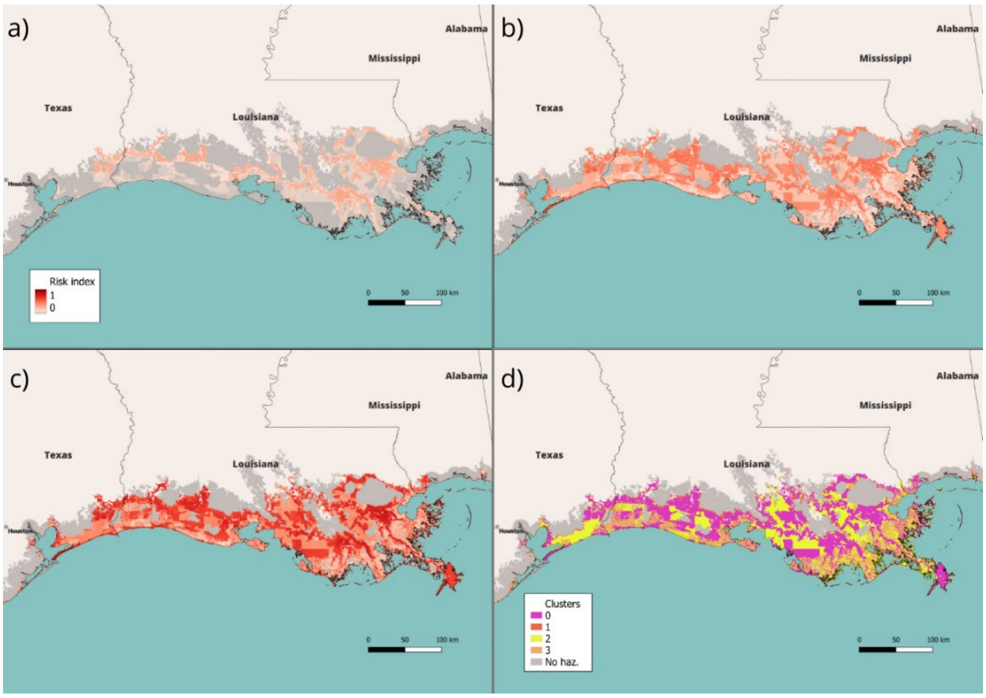

Fig. 4: Gulf of Mexico. *Panels a), b), c), and d) represent optimistic, neutral, and pessimistic scenarios and clustering results, respectively.*

3. Conclusions

Reliable and comparable data for the entire world are essential for planning adaptation policies and guiding the allocation of financial resources available through international agreements, such as the Climate Adaptation Fund. A preliminary requirement for resource allocation is the identification of risk levels in present conditions and future projections. The current analysis involved the selection of data with the necessary characteristics to provide not only an estimation of risk under different scenarios but also a classification of the main combinations of features. The proposed method can guide the identification of specific strategies and commonality of issues around the world.

The representation of risk attitudes and its combination with different scenarios in the context of global coastal risk is a novel aspect of the present study. This approach has the potential to increase the meaningfulness and realism of scenario analysis by combining the assumptions of climate simulations and scenarios with coherent assumptions in terms of risk attitudes. The spatial resolution adopted provides a level of granularity that goes beyond most recent studies, particularly regarding the social and economic variables adopted for the calculation of the E and V sub-indices. The findings indicate that the evolution of risk in the future will significantly depend on the interactions between evolving hazards and local trends in terms of the value of exposed assets (E) and the combination of physical and socioeconomic features (V).

Additionally, the applied methods revealed that estimated risk increases are highly uneven across the world. Risk hot spots, here defined as the areas with a risk index higher than the 99th percentile, are already present at baseline in western Europe and south-eastern Asia, while they appear in the rest of Asia under the RCP4.5-SSP2 scenario and in the Americas, Australia, and Africa only under the RCP8.5-SSP5 scenario. As a global trend, larger risk hot spots appear not only in the pessimistic scenario but also in the RCP4.5-SSP2 scenario, indicating that risks will increase even with relatively neutral assumptions about the future.

The current results have clear implications for global climate policies by allowing for the identification of the location and magnitude of risks and their future evolution, thus defining where adaptation strategies are more urgent. Additionally, our findings suggest the need for various countries to accurately monitor both climatic and socioeconomic trends because of the vast areas that may become at risk even in a relatively neutral, non-pessimistic scenario.

Importantly, the proposed method is not supposed to substitute local-scale analyses with more detailed data, and it should be emphasised that risk and vulnerability are scale-sensible (Rocha et al., 2023). Using comparable data at a global scale can highlight areas that warrant further analysis. Moreover, the methodologies employed in the current study can be directly applied to local contexts.

The amount and quality of spatial data with global coverage and the results of scenario analyses are rapidly growing. Future improvements may be enabled by the adoption of improved flood modelling outputs and increased availability of accurate spatial digital surface models with global coverage, allowing consideration of existing or planned defence infrastructure affecting local vulnerabilities and improving the mapping of exposed assets. Therefore, revisions and improvements to the results presented herein can be expected in the near future, also thanks to the algorithm and the code made freely available in the supplementary materials.

4. Acknowledgments

We gratefully acknowledge the financial support of Fondazione Eni Enrico Mattei (FEEM), Climate Change Adaptation (ADAPT@VE) Programme and pf Ca' Foscari University of Venice. We thank the experts who provided weight vectors for the multi-criteria analysis, and Timothy Tiggeloven who shared the flood hazard data.

This article was developed within the project funded by Next Generation EU - "GRINS - Growing Resilient, INclusive and Sustainable" project (PE0000018), National Recovery and Resilience Plan (NRRP) – PE9 - Mission 4, C2, Intervention 1.3". The views and opinions expressed are only those of the authors and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the European Commission can be held responsible for them.

Author contributions: M.B. methodology, software, formal analysis; C.G. supervision, validation, funding acquisition, projects administration; both: resources, conceptualisation, methodology, visualisation and writing.

5. Declaration of interests

The authors declare no competing interests.

6. Data availability statement

Supplementary materials, codes and data can be downloaded from:

https://doi.org/10.6084/m9.figshare.29077709.v3

7. References

ADDY, J. W. G., ELLIS, R. H., MACDONALD, A. J., SEMENOV, M. A. & MEAD, A. 2021. Changes in agricultural climate in South-Eastern England from 1892 to 2016 and differences in cereal and permanent grassland yield. *Agricultural and Forest Meteorology,* 308-309**,** 108560.

ALANIZ, A. J., SMITH-RAMÍREZ, C., RENDÓN-FUNES, A., HIDALGO-CORROTEA, C., CARVAJAL, M. A., VERGARA, P. M. & FUENTES, N. 2022. Multiscale spatial analysis of headwater vulnerability in South-Central Chile reveals a high threat due to deforestation and climate change. *Science of The Total Environment,* 849**,** 157930.

ATHANASIOU, P., VAN DONGEREN, A., PRONK, M., GIARDINO, A., VOUSDOUKAS, M. & RANASINGHE, R. 2024. Global Coastal Characteristics (GCC): a global dataset of geophysical, hydrodynamic, and socioeconomic coastal indicators. *Earth Syst. Sci. Data,* 16**,** 3433-3452.

CIAN, F., GIUPPONI, C. & MARCONCINI, M. 2021. Integration of earth observation and census data for mapping a multi-temporal flood vulnerability index: a case study on Northeast Italy. *Natural Hazards,* 106**,** 2163-2184.

DÍAZ GONZÁLEZ, C. A., MENDEZ CALDERÓN, Y. M., MOJICA CRUZ, N. A. & PACHECO SANDOVAL, L. E. 2022. Typologies of Colombian off-grid localities using PCA and clustering analysis for a better understanding of their situation to meet SDG-7. *Cleaner Energy Systems,* 3**,** 100023.

FARRIS, F. A. 2010. The Gini index and measures of inequality. *American Mathematical Monthly,* 117**,** 851.

FULLÉR, R. 1996. OWA Operators in Decision Making. *Exploring the Limits of Support Systems.* Turku Centre for Computer Science.

GIUPPONI, C., MOJTAHED, V., GAIN, A., BISCARO, C. & BALBI, S. 2015. Integrated Risk Assessment of Water-Related Disasters.

GUL, F. & PESENDORFER, W. 2014. Expected Uncertain Utility Theory. *Econometrica,* 82**,** 1-39.

HAASNOOT, M., WINTER, G., BROWN, S., DAWSON, R. J., WARD, P. J. & EILANDER, D. 2021. Long-term sea-level rise necessitates a commitment to adaptation: A first order assessment. *Climate Risk Management,* 34**,** 100355.

HINKEL, J., LINCKE, D., VAFEIDIS, A. T., PERRETTE, M., NICHOLLS, R. J., TOL, R. S. J., MARZEION, B., FETTWEIS, X., IONESCU, C. & LEVERMANN, A. 2014. Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proceedings of the National Academy of Sciences,* 111**,** 3292-3297.

IPCC 2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change*.

IPCC 2019. Sea level rise and implications for low-lying islands, coasts and communities. *The Ocean and Cryosphere in a Changing Climate.* Cambridge University Press.

IPCC 2023. *Climate Change 2022 – impacts, adaptation and vulnerability*, Cambridge University Press.

JRC 2011. *Coastal Zones: Policy Alternatives Impacts on European Coastal Zones 2000-2050*, Dictus Publishing.

KAISER, H. F. 1960. The Application of Electronic Computers to Factor Analysis. *Educational and Psychological Measurement,* 20**,** 141-151.

KETCHEN, D. J. & SHOOK, C. L. 1996. THE APPLICATION OF CLUSTER ANALYSIS IN STRATEGIC MANAGEMENT RESEARCH: AN ANALYSIS AND CRITIQUE. *Strategic Management Journal,* 17**,** 441-458.

KHANAL, S., RIDDER, N., DE VRIES, H., TERINK, W. & VAN DEN HURK, B. 2019. Storm Surge and Extreme River Discharge: A Compound Event Analysis Using Ensemble Impact Modeling. *Frontiers in Earth Science,* 7.

KIREZCI, E., YOUNG, I., RANASINGHE, R., CHEN, Y., ZHANG, Y. & RAJABIFARD, A. 2025. Global Dataset of Extreme Sea Levels and Coastal Flood Impacts over the 21st Century. *Data* [Online], 10.

KIREZCI, E., YOUNG, I. R., RANASINGHE, R., LINCKE, D. & HINKEL, J. 2023. Global-scale analysis of socioeconomic impacts of coastal flooding over the 21st century. *Frontiers in Marine Science,* 9.

LEMPERT, R. J. 2019. Robust Decision Making (RDM). *In:* MARCHAU, V. A. W. J., WALKER, W. E., BLOEMEN, P. J. T. M. & POPPER, S. W. (eds.) *Decision Making under Deep Uncertainty: From Theory to Practice.* Cham: Springer International Publishing.

MCGRANAHAN, G., BALK, D. & ANDERSON, B. 2007. The Rising Tide: Assessing the Risks of Climate Change and Human Settlements in Low Elevation Coastal Zones. *Environment and Urbanization - ENVIRON URBAN,* 19**,** 17-37.

REIMANN, L., VAFEIDIS, A. T., BROWN, S., HINKEL, J. & TOL, R. S. J. 2018. Mediterranean UNESCO World Heritage at risk from coastal flooding and erosion due to sea-level rise. *Nature Communications,* 9**,** 4161.

ROCHA, C., ANTUNES, C. & CATITA, C. 2023. Coastal indices to assess sea-level rise impacts - A brief review of the last decade. *Ocean & Coastal Management,* 237**,** 106536.

SATTA, A., PUDDU, M., VENTURINI, S. & GIUPPONI, C. 2017. Assessment of coastal risks to climate change related impacts at the regional scale: The case of the Mediterranean region. *International Journal of Disaster Risk Reduction,* 24**,** 284-296.

SAVAGE, L. J. 1954. *The foundations of statistics,* Oxford, England, John Wiley & Sons.

SCUSSOLINI, P., AERTS, J. C. J. H., JONGMAN, B., BOUWER, L. M., WINSEMIUS, H. C., DE MOEL, H. & WARD, P. J. 2016. FLOPROS: an evolving global database of flood protection standards. *Nat. Hazards Earth Syst. Sci.,* 16**,** 1049-1061.

TANIM, A. H., GOHARIAN, E. & MORADKHANI, H. 2022. Integrated socio-environmental vulnerability assessment of coastal hazards using data-driven and multi-criteria analysis approaches. *Scientific Reports,* 12**,** 11625.

TIGGELOVEN, T., DE MOEL, H., WINSEMIUS, H. C., EILANDER, D., ERKENS, G., GEBREMEDHIN, E., DIAZ LOAIZA, A., KUZMA, S., LUO, T., ICELAND, C., BOUWMAN, A., VAN HUIJSTEE, J., LIGTVOET, W. & WARD, P. J. 2020. Global-scale benefit–cost analysis of coastal flood adaptation to different flood risk drivers using structural measures. *Nat. Hazards Earth Syst. Sci.,* 20**,** 1025-1044.

TORRA, V. 1997. The weighted OWA operator. *International Journal of Intelligent Systems,* 12**,** 153-166.

UNEP 2002. Global Risk And Vulnerability Index Trends per Year (GRAVITY) Phase II: Development, analysis and results.

UNEP 2021. The Adaptation Gap Report 2021: United Nations Environment Programme (UNEP).

VAFEIDIS, A. T., NICHOLLS, R. J., MCFADDEN, L., RICHARD, R. J. T., HINKEL, J., SPENCER, T., GRASHOFF, P. S., BOOT, G. & KLEIN, R. J. T. 2008. A New Global Coastal Database for Impact and Vulnerability Analysis to Sea-Level Rise. *Journal of Coastal Research,* 2008**,** 917-924.

WOLFF, C., VAFEIDIS, A. T., MUIS, S., LINCKE, D., SATTA, A., LIONELLO, P., JIMENEZ, J. A., CONTE, D. & HINKEL, J. 2018. A Mediterranean coastal database for assessing the impacts of sea-level rise and associated hazards. *Scientific Data,* 5**,** 180044.

ZHANG, Z., HU, B. & QIU, H. 2021. Comprehensive assessment of ecological risk in southwest Guangxi-Beibu bay based on DPSIR model and OWA-GIS. *Ecological Indicators,* 132**,** 108334.

FONDAZIONE ENI ENRICO MATTEI WORKING PAPER SERIES

Our Working Papers are available on the Internet at the following address:
https://www.feem.it/pubblicazioni/feem-working-papers/

"NOTE DI LAVORO" PUBLISHED IN 2026

1. R. Corbi, C. Falco, L. J. Uberti, Dams and Rural Conflict: Evidence from Brazil's Hydropower Expansion
2. A. Bastianin, L. Rossini, A. Testa, Industrial Metal Supply Shocks and Heterogeneous Macroeconomic Effects: Evidence from Copper
3. C. Casoli, R. Lucchetti, A rotated Dynamic Factor Model for the yield curve: squeezing out information when it matters

Fondazione Eni Enrico Mattei
Corso Magenta 63, Milano – Italia

Tel. +39 02 403 36934

E-mail: letter@feem.it
www.feem.it

FONDAZIONE ENI ENRICO MATTEI