Doctoral Dissertation
Doctoral Program in Urban and Regional Development (37^{th}cycle)

Assessing Vulnerability to Rapid-Onset Coastal Flooding:

Advancing Methodological Approaches with a Focus on the Mediterranean Sea Basin.

By

Alice Re

******

Supervisor(s):
Prof. Dr. Alessandro Pezzoli, Supervisor
Dr. Lorenzo Minola, Co-Supervisor

Doctoral Examination Committee:
Prof. Dr. Faith Chan, Referee, University of Nottingham – Ningbo – China
Prof. Dr. Maria Teresa Melis, Referee, Università di Cagliari
Dr. Cesar Azorin-Molina, Climatoc-Lab - CIDE Spanish National Research Council
Prof. Dr. Giandomenico Fubelli, Università di Torino
Prof. Dr. Marco Piras, Politecnico di Torino

Politecnico di Torino
2025

Declaration

I hereby declare that, the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

Alice Re
2025

* This dissertation is presented in partial fulfillment of the requirements for **Ph.D. degree** in the Graduate School of Politecnico di Torino (ScuDo).

The Jurassic Park soundtrack theme plays in the background.

Acknowledgements

I would like to acknowledge the people who have supported me with great professionalism and equally great kindness throughout this experience.
I will be forever grateful to my supervisors, Alessandro and Lorenzo, for their gracious support while allowing me to pursue my own interests at my own pace. Their trust in letting me explore was truly decisive in making this experience a true adventure of curiosity for me, deeply rooted in the joy of discovery. I would wish this on any young researcher.
I am grateful to the referees who have taken the time to read this thesis and have made comments to improve it. I would like to thank all the members of the PhD Committee for taking the time to attend the final examination and discuss my work. I am truly thankful to have been given the opportunity to access such an educational opportunity, and I will always be grateful to all the fellow researchers who shared their knowledge with me both formally during the courses and informally through useful inputs. I am glad to have had the opportunity to travel to pursue my research interests throughout this experience, and especially to have had the chance to join the University of Valencia for a while.
This journey would not have been as light-hearted as it has been without the continued support and dose of humour provided by my fellow PhD comrades. To the Truffles, a heartfelt thank you for creating a much needed sense of community during these challenging years.
Finally, as I write these final words of my PhD thesis, I am grateful to have persevered through challenging times to reach the end of this journey. Perseverance was very much a product of a support ecosystem made by the people that are close to me in my personal life. To them I express a deep and heartfelt thank you for helping me get to this point.

Abstract

Increased storminess associated with climate change poses a significant threat in terms of the potential to generate rapid-onset flooding in coastal areas. Vulnerability to such events is the result of a combination of natural and socio-economic factors. On the natural hazards side, the location of coastal areas at the interface between terrestrial and marine ecosystems makes them particularly vulnerable to all major flood drivers. Among these, extreme sea level change a particularly uncertain driver, with a high degree of uncertainty in its future development, which will be exacerbated by the rise in mean sea level. On the other hand, coastal areas worldwide are densely populated and contain many potentially vulnerable human assets.

The Mediterranean Sea basin is a good example of this double criticality, in that there is uncertainty about future extreme sea levels in this area on the one hand, and on the other, it has historically been very densely populated in proximity to the coasts because of its micro-tidal character.

A variety of methodologies for assessing coastal flood vulnerability have been developed in the literature, each of which raises a number of critical issues from both a theoretical and practical implementation perspective. The aim of this thesis is to analyse the potential and the scope of application of some of these methodologies for the Mediterranean Sea basin, examining their strengths and weaknesses and exploring some of their aspects that are underdeveloped in the literature. In order to achieve these objectives, the thesis is structured around three main pillars.

The first part of the thesis provides a solid theoretical and methodological foundation on the main methods for modelling and mapping rapid onset flooding in coastal areas, in order to provide a general framework within which to place the rest of the analyses.

In the second part of the thesis, an indicator-based method is used to assess coastal vulnerability to flooding, exploring in particular its potential for the development of different climate change scenarios. The results of the analysis show that this method is suitable for obtaining first-order assessments, but that it is characterised by a number of critical issues in relation to the processes of aggregation and computation of the indicators, which may represent significant limitations in its use as a decision support tool.

In the third part of the thesis, the scope of application of data-driven methods in flood research is explored. An analysis for the assessment of coastal flood susceptibility for the study area is developed as a supervised classification method using modelled ground truth data for model training. The results of the analysis show how such approaches can lend themselves to identifying areas susceptible to flooding in coastal zones with topological characteristics similar to that of the study area. Future research directions are highlighted with regard to the need to generalise the approach for coastal zones of different conformation and obtain more precise results in the future.

This thesis contributes to the development of research in the area of vulnerability assessment to the consequences of climate change in general and coastal flooding specifically, whereby some new limitations are highlighted and some areas for potential future research developments are explored, with a focus on decision support for increasing coastal resilience to climate change.

Appended Papers

This dissertation is based on the following scientific papers. The papers are included in Appendix A and are referred to in the text by their Roman numerals. They are either reprinted in their original form where applicable, or included as the final draft ready for submission to a scientific journal.

Paper I: Modelling and Mapping Rapid-Onset Coastal Flooding: A Systematic Literature Review
Re, Alice; Minola, Lorenzo; Pezzoli, Alessandro. *Water* **2025**, 17(4), 599. DOI:10.3390/w17040599

Paper II: Climate Scenarios for Coastal Flood Vulnerability Assessments: A Case Study for the Ligurian Coastal Region
Re, Alice; Minola, Lorenzo; Pezzoli, Alessandro. *Climate* **2023**, 11, 56. DOI:10.3390/cli11030056

Paper III: A Machine Learning Approach to the Identification of Areas Susceptible to Compound Coastal Flooding
Re, Alice; Minola, Lorenzo; Camps-Valls, Gustau; Pezzoli, Alessandro. *Article ready for submission to Natural Hazards.*

Contributions: The selected studies are the result of co-authorships, reflecting the collaborative nature of the research behind them. In **Paper I**, A. Re led the phases of study design, data analysis, writing and revision. In **Paper II**, A. Re contributed to the definition of the study design and data analysis, and led the writing and revision phases. In **Paper III**, A. Re contributed to the definition of the study design, and led the data analysis, writing and revision phases.

Contents

List of Figures

List of Tables

Nomenclature

Acronyms / Abbreviations

CCVA Climate Change Vulnerability Assessment

CEMS Copernicus Emergency Management Service

CES Constant Elasticity Substitution

CVI Coastal Vulnerability Index

DEM Digital Elevation Model

DII Difference Image Index

DIVA Dynamic and Interactive Vulnerability Assessment

DRR Disaster Risk Reduction

DSPRC Driver-Source-Pathway-Receptor-Consequences

DSS Decision-Support System

ESL Extreme Sea Level

EU European Union

EWS Early Warning System

GEE Google Earth Engine

GFM Global Flood Monitoring

GIS Geographic Information System

GloFAS Global Flood Awareness System

IBVA Indicator-based Vulnerability Assessment

ICZM Integrated Coastal Zone Management

IPCC Intergovernmental Panel on Climate Change

MCDA Multi Criteria Decision Analysis

ML Machine Learning

MNDWI Modified Normalized Difference Water Index

NDFI Normalised Difference Flood Index

PMP Prevention, Mitigation and Preparedness

RI Ratio Index

RVA Regional Vulnerability Assessment

SAR Synthetic Aperture Radar

SES Socio-Ecological System

SLR Sea Level Rise

TAR Third Assessment Report

Chapter 1

Background

The Mediterranean Sea basin has been identified as one of the areas which will suffer the most severe consequences of climate change globally [4]. Among these, flooding caused by disruptions of the hydrological cycle and meteo-oceanic extreme events is expected to be most impactful in terms of affected population and potential damage. Its nature as a semi-enclosed sea basin and the consequent near-absence of tides has led to the establishment of densely populated and urbanised settlements in Mediterranean coastal areas, in close proximity to the modern day mean sea level. There is high uncertainty in the understanding of future extreme sea level changes and marine inundation in the Mediterranean. Even though research has pointed towards a likely decrease in the magnitude and frequency of extreme sea level events, the increase in average sea level will likely be sufficient to more than compensate the coastal flooding risk to which coastal communities in the Mediterranean will be exposed. This dissertation is aimed at improving the understanding of vulnerability to rapid-onset coastal flooding in the Mediterranean Sea basin, including coastal flooding associated to extreme sea levels (ESLs).

Vulnerability to climate change is defined in the Third Assessment Report (TAR) of the Intergovernmental Panel on Climate Change (IPCC) as *"the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity and its adaptive capacity"* [5].

Even though since its first definition there has been confusion in the interpretation of the concept, it is generally widely acknowledged that vulnerability stems from the interaction within complex systems of natural and anthropic elements, and that both components are fundamental in characterising it. This conceptual complexity is in turn mirrored by the multifaceted set of methodologies that have been developed to assess vulnerability and to operationalise its implementation within mitigation and adaptation policies aimed at improving societal resilience to climate change.
The way in which data is collected and processed to generate actionable information, which components of vulnerability are addressed in different methodologies and the underlying methodological assumptions utilised to evaluate it are at the forefront in shaping the decisions that are made on how to address societal response to climate change. The definition of the scope of application of different methodologies for the assessment of vulnerability to coastal flooding is the lens through which this dissertation can be interpreted. It aims at mapping the state of the art of literature in the field, and to test the extent to which different methodologies can be modified and adapted in light of the ever-evolving sets of new information and technologies that become available, and to understand the ensuing implications of such modifications for the purpose of informing policy decisions.
Even though the primary aim of the developed research was methodological, a choice was made to refer specifically to the Italian coastal region Liguria as the study area within which to test the various methodologies addressed. In turn, this has also resulted in the improvement of the knowledge field of coastal vulnerability in this specific area within the Mediterranean Sea basin.

1.1 Vulnerability to Climate Change

The concept of vulnerability is the theoretical foundation upon which this dissertation is based. As mentioned before, vulnerability is a a complex and multifaceted concept, which has proven elusive since its inception. To this day, relevant literature contributions have analysed and highlighted the state of *Babylonian confusion* surrounding the concept in both research and policy [6].
The very TAR IPCC definition of vulnerability as a composite of exposure, sensitivity and adaptive capacity has been identified as being among the root causes of such confusion. Difficulties in a precise definition and subsequent potential operationalisation

of vulnerability stemmed from a twofolod fault, pertaining to both the vagueness of the defining concepts themselves and from the uncertainty in how they should be combined to define vulnerability.
Hinkel [6] proposed a comprehensive analysis of research on vulnerability to climate change, emphasizing the variety in approaches and concluding that a limited number of common elements could be found across the majority of studies. Among these, most definitions and vulnerability methodologies concurred in considering vulnerability as *a measure of possible future harm* for an entity. Several implications arise from this consideration.

Firstly, that vulnerability is defined with reference to a specific system. In most cases, climate change vulnerability assessments reference composite socio-ecological systems (SESs [7]), defined based on the interrelations between the human and natural components *with connections operating at different spatiotemporal scales and commonly involving stochastic and nonlinear processes* [8]. Further considerations should then be made pertaining to the delimitation of such a system, as *comprehensive vulnerability analysis ideally considers the totality of the system* [8]. Though, real-world constraints require the development of *reduced* vulnerability assessments, also based on the local context and data availability.
The necessity to clarify the definition of which reduced-form of SES one wants to adopt when addressing vulnerability can be further highlighted by contextualising the theoretical vulnerability concept within the subject matter of this dissertation. When referring to the vulnerability of coastal systems, a series of potential stressors for which to assess vulnerability have been addressed in literature. Research carried out in the initial phases of the development of work for **Paper I** entailed a series of rounds of informal literature search in order to define the keywords to use for the systematic search. This work allowed to highlight that the use of the keywords *coastal vulnerability* was very widespread in the literature and was associated with variable and inconsistent sets of potential stressors, as well as inconsistencies in the definition of the SES elements addressed. In many cases, research articles did not clarify whether the study addressed vulnerability to flooding, erosion or a mix of both.

Second and third tiers of implications arising from considering vulnerability as a measure of possible future harm pertain respectively to the forward-looking aspect of vulnerability and to the definition of harm.

The former aspect is the pivotal element which differentiates vulnerability as a forward-looking concept from harm – and indicators thereof – as a measure of the current state of an entity. On the other hand, the definition of harm is related to *a value judgment on the badness of a state* [6], thus introducing a further potentially subjective and fuzzy layer of indefinitiveness to the concept.
Eriksen and Kelly [9] identified that one key distinction in vulnerability research has emerged between end-point and starting-point vulnerability. In the first case, vulnerability is considered as the end point of the analysis in the sense that it denotes *the residual climate change impacts once adaptation has occurred*. This interpretation of vulnerability in turns results in the framing of potential adaptive options as *fixes* aimed at the minimisation of the impacts of climate change upon a system, subsequently resulting in a reduced pool of policy options up for consideration, often technological in nature. On the other end, the interpretation of vulnerability as a starting-point of the analysis entails considering it as *a pre-existing state generated by multiple factors and processes*. This interpretative lens to the concept is then translated in a wider array of policy options to be considered, as they are aimed not only at fixing a problem but also at addressing the root causes and drivers of vulnerability.

It was highlighted above that for the concept of vulnerability the consideration of the temporal scale of reference is particularly relevant, as the concept is referred to a potential future and not to a current state of events. Adopting a temporal perspective is also necessary when making another distinction identified by Eriksen and Kelly [9], that between the processes of coping and adaptation. While the former refers to policies developed within a short-term horizon and aimed at restoring the system state previous to the suffered harm, adaptation refers to a long-term process which entails the reconfiguration of the functioning of the system itself, *aimed at attaining an evolving change in state* [9]. This differentiation is not only a theoretical concept but can have possible tangible consequences, as the policy instruments related to coping and adaptation might be radically different.

Such considerations on the restoration of a previous state of a system or its evolution towards a new modified equilibrium are also linked to the concept of resilience. While older definitions of resilience referred to it as the ability of a system to revert to its original state before a stressor, more recent interpretation have acknowledged that ecosystems can exhibit multi-equilibria dynamics. As a consequence, resilience can be defined as *the amount of change a given system can undergo (e.g., how much disturbance or stress it can handle) and still remain within the set of natural or desirable states (i.e., remain within the same "configuration" of states, rather than maintain a single state)* [8]. It must be noted that resilience has been recognised in literature as being closely related to vulnerability, and that it is sometimes referred to as *the flip side of vulnerability*, thus representing a sort of complementary concept thereof [10]. The differences between the two concepts are likely related to their disciplinary origin, coming mostly from the fields of natural hazards and geography for vulnerability and from the fields of ecology and mathematics for resilience [11]. Having acknowledged this, no further mention of resilience will be made in the remainder of this dissertation, only referring to vulnerability henceforth.

Even if several issues have been highlighted in this section, vulnerability can still represent a useful lens though which to frame the potential impacts of climate change on SESs. Within this outlook, it is fundamental to approach both the theoretical discussions on the concept and its operationalisation in research and policy with a cognizant perspective, while acknowledging that *the one-size-fits-all vulnerability label* might be limiting [6].

1.2 Operationalisation of the Concept of Vulnerability: Methods

As measuring is related to observable phenomena, some authors have highlighted that vulnerability cannot be measured since it is a theoretical concept. In turn, *making a theoretical concept operational consists in providing a method (an operation) for mapping it to observable concepts* [6]. Therefore, methodologies aimed at assessing vulnerability represent options for the operationalisation of the concept of vulnerability [6]. From the definition of vulnerability as a combination of exposure, sensitivity and adaptive capacity stemmed one relevant methodological consequence for its operationalisation. Namely, the combination of this clear-cut distinction among components and the lack of a clear defining function establishing how these effectively combine in determining overall vulnerability caused a significant portion of vulnerability assessments to focus on assessing the three components of vulnerability separately without addressing their fundamental interrelations [6]. Nevertheless, previous literature emphasized the fundamental importance of defining the linkages between the human and environmental components of SESs in order to be able to grasp the potential impact of perturbations happening to such linkages – one such example was proposed within the framework for vulnerability assessment developed by Turner et al. [8].

Within a thorough analysis of the state-of-the-art of vulnerability assessment methodologies, Tonmoy et al. [10] defined climate change vulnerability assessments (henceforth, CCVAs) as *any attempt at assessing vulnerability to climate change, be it quantitative or qualitative*. It should be highlighted that the very term *assessment* denotes its final function in terms of applicability to support problem-solving and decision making, and can therefore in theory be differentiated from research, as the latter denotes instead the advancement of knowledge for its intrinsic value rather than for a specific application [6].
CCVAs can be radically different in terms of both their characteristics and their envisioned scope of application. Tonmoy et al. [10] identified four main types of CCVA: i) simulation-based assessments, ii) aggregation-based assessments, iii) hybrid approaches (simulation + aggregation), iv) no simulation and/or no aggregation approaches. All these broad types of CCVA are backed by theoretical studies.

Methodological hindrances have been highlighted in literature pertaining to all main types of CCVA methodologies identified. For instance, Hinkel [6] highlighted some drawbacks in the development of statistical methods for vulnerability assessment, as such approaches require in general to be able to define the system which is being addressed in a narrow way and with a reduced set of variables, which we have highlighted above as being particularly difficult for complex SESs and uncertain climate change-related processes. Some of the methodological limitations related to the process of aggregation in vulnerability assessment methodologies are proposed in Section 3. **Paper I** contributed to the identification of some methodological limitations related to a broad series of different methodologies utilised to assess vulnerability to rapid-onset flooding in coastal areas. A more specific focus was adopted instead in **Paper II**, in which an indicator-based vulnerability assessment methodology was utilised for the area of interest described in Section 1.4. An in-depth

discussion of strengths and limitations of indicator-based vulnerability assessment methodologies is proposed in Section 3.
Vulnerability is highly variable in space [8], which has caused methodologies to develop, evolve and multiply for the specific purpose of being applied at different scales [6]. Within this context, *place-based* vulnerability assessment methodologies are particularly relevant, as the specificity of the location can determine the local outcome of global-scale processes. Even though place-based assessments are essential, Turner et al. [8] emphasized that their importance should not lead to excluding or neglecting more extensive research with a wider scope. Rather, place-based assessments should be used to build and identify general concepts common to all of them, even though this has been shown to be a difficult task [6].
The shape of the specific vulnerability assessment methodology is furthermore defined, along with the conception/specific interpretation of vulnerability adopted, by the desired role and utilisation of the assessment itself. Such roles include the identification of vulnerable hotspots, resource allocation, proving guidance in the choice of potential adaptation options, contributing to the identification and explanation of structural weaknesses, drafting and communicating risk-related policies [10].

In the remainder of this work, several approaches to the assessment of vulnerability will be investigated more in depth, with a focus on rapid-onset coastal flooding. Namely, the following aspects will be addressed:

1. The end-goal of vulnerability assessments as a decision support tool has been addressed above in this dissertation. Communication of relevant flood-related information can be interpreted as a twofold concept pertaining both to the way research interfaces with decision makers to communicate its findings, and how these are in turn utilised and communicated by decision makers. Flood modelling and mapping applications represent essential research outcomes that give substance and make evident this communication, and are essential CCVA-related tools overall. These topics are analysed in Chapter 2 and **Paper I**, adopting a broad methodological perspective.

2. Chapter 3 and **Paper II** refer to a specific category of comprehensive CCVA approaches, that of indicator-based vulnerability assessment methodologies. A more in-depth investigation of this class of approaches is presented therein, referring to previous literature as well as to the findings stemming from the

case study presented in the article. A focus on the spatial representation of indicator-based flood vulnerability assessment methodologies is also proposed.

3. Some significant methodological hindrances were encountered during the development of **Paper II**. As a consequence, Chapter 4 and **Paper III** adopt a more circumscribed approach to the analysis of potential consequences of flooding in coastal areas. Specifically, a focus on flood susceptibility assessment through data-driven methodologies is adopted there. This reduction in scope can be inscribed within the aforementioned argument concerning the need to abandon the *one-size-fits-all* vulnerability label [6], and is paralleled by improvements in the spatial representation of the research outputs.

Alongside this methodological overview, the research presented in this dissertation was articulated to address more specific research questions, which are outlined in Section 1.5.

1.3 The Mediterranean as a Hotspot for Climate-Related Risks

Due to its location in a transition zone between the temperate mid-latitude and sub-tropical (hotter and dryer) atmospheric regimes, the Mediterranean Sea basin is highly sensitive to climate change-related disruptions of the hydrological cycle, including strong precipitation and flash floods, strong winds, large swells and storm surges, heatwaves and droughts [12–14].
Current surface temperature in the Mediterranean region has already surpassed the pre-industrial level mark by 1.5°C, and the sea surface has risen by 0.29°C-0.44°C every decade since the early 1980s. During the 20th century the sea level has increased every year by 1.4±0.2mm, and it has been estimated with high confidence that the quasi-homogeneous signal of global mean sea level rise combined with changes in the northeast Atlantic circulation will cause it to continue to rise in the coming decades and centuries: 0.15-0.33 m in the year 2050 and between 40 and 100 cm at the end of the 21st century [14] and that this process will be irreversible at the scale of centuries to millennia [4].
When it comes to the threats of climate change to coastal communities related to increased sea levels, though, it is of notable importance how the increase in the

average sea level is not going to pose the major risks, but rather the extended reach of the extreme sea levels and rapid-onset flooding ensuing from it are. Studying within-region variability comes with challenges related to the quality of past observations and data coverage which is heterogeneous between northern and southern countries in the region [13], to the limits of climate models applied to the Mediterranean [4, 15–17] and to the importance of the strong regional characterisation of the areas of cyclogenesis [18]. Nevertheless, projected changes of climate variables relevant to rapid-onset coastal flooding such as winds, storms and waves are predicted to be small [4], and notable literature has pointed towards a reduction in the average number [19] and magnitude [20] of positive surges and towards lower values of extreme wind waves [21] related to the generation of extreme sea levels in the Mediterranean sea basin.
The projected sea level rise is likely to increase the risk of coastal flooding nonetheless, even considering the expected slight decrease in marine storms [4, 17]. Absolute coastal flooding risk is projected to increase strongly in the future also due to a combination of climate-related sea level variations with socioeconomic drivers if coastal protection structures remain unchanged in the future [22]. For these reasons, the socioeconomic characterisation is equally as important as the study of climate variation and coastal flood hazards to achieve a comprehensive view of vulnerability to coastal flooding in the Mediterranean Sea basin.

Among the reasons at the base of the Mediterranean region being considered a hotspot for vulnerability to climate variation and flooding specifically [23, 4], is the presence of dense population settlements in close proximity to the coastline and to current average sea levels, whose establishment has historically been favoured by the micro-tidal character of the sea basin [12]. The specific conformation of the inland systems upon which the coastal flood hazard acts is of paramount importance in determining the overall vulnerability and risk of rapid-onset coastal flooding.
A popular philosophical thought experiment about the possibility of unperceived existence raises the question of whether a tree falling in a forest, with no one around to witness it, still makes a sound. Whereas on the philosophical side the question is debated, on the climate risk side the answer is much clearer: in the absence of someone to experience it, a hazard does not conform as a risk. On the other side of the spectrum, for certain socioeconomic and natural configurations of coastal communities, even small marine hazards might represent non-negligible risks.

Research has highlighted how for some Mediterranean coastal communities the adaptation options to climate change are limited, and how the risk to suffer severe impacts from extreme marine storms will further be aggravated by the loss of beaches and other natural coastal ecosystems that are instrumental in dampening the effects of coastal storms and inundation, but which in the future might be lost to the erosion caused by rising sea levels [24].

The physical predisposition of a system to be negatively affected by a dangerous phenomenon and suffer its consequences due to its intrinsic characteristics is commonly referred to as susceptibility (see Chapter 4). Some coastal areas might be characterised by specific topographic and geomorphological conformations that might make them susceptible to variable combinations of marine-driven inundation and flooding of pluvial and fluvial origin [25, 26]. Specifically, low-lying coasts and especially estuaries have been widely studied in literature because their topographic conformation and location at the interface between the outlets of complex fluvial networks and the sea can result in interactions between different flood drivers and eventually in episodes of compound flooding.
Diametrically opposed to those just mentioned, some other coastal areas are instead characterised as narrow strips of land nestled between the mountains and the sea. Their shape and topographic conformation – rough terrain, small watersheds – make them vulnerable especially to storms that might generate combinations of pluvial flash-flooding events and marine inundation. The Italian coastal region Liguria represents such an example, and it was chosen as a study area for some of the methodologies analysed in this dissertation specifically because of this reason.

1.4 Study Area

The Italian region of Liguria (Figure 1.1) was utilised as a study area for some of the methodologies addressed in this dissertation, and notably for the case studies developed in **Paper II** and **Paper III**. Liguria is a narrow coastal region nestled between the mountains and the sea in the North-Western Mediterranean basin, characterised by low-lying areas located predominantly in the western side of the region and by cliffs and high coasts in the eastern side. The most significant urban areas of the region are located at low elevations and in proximity to both the sea and river

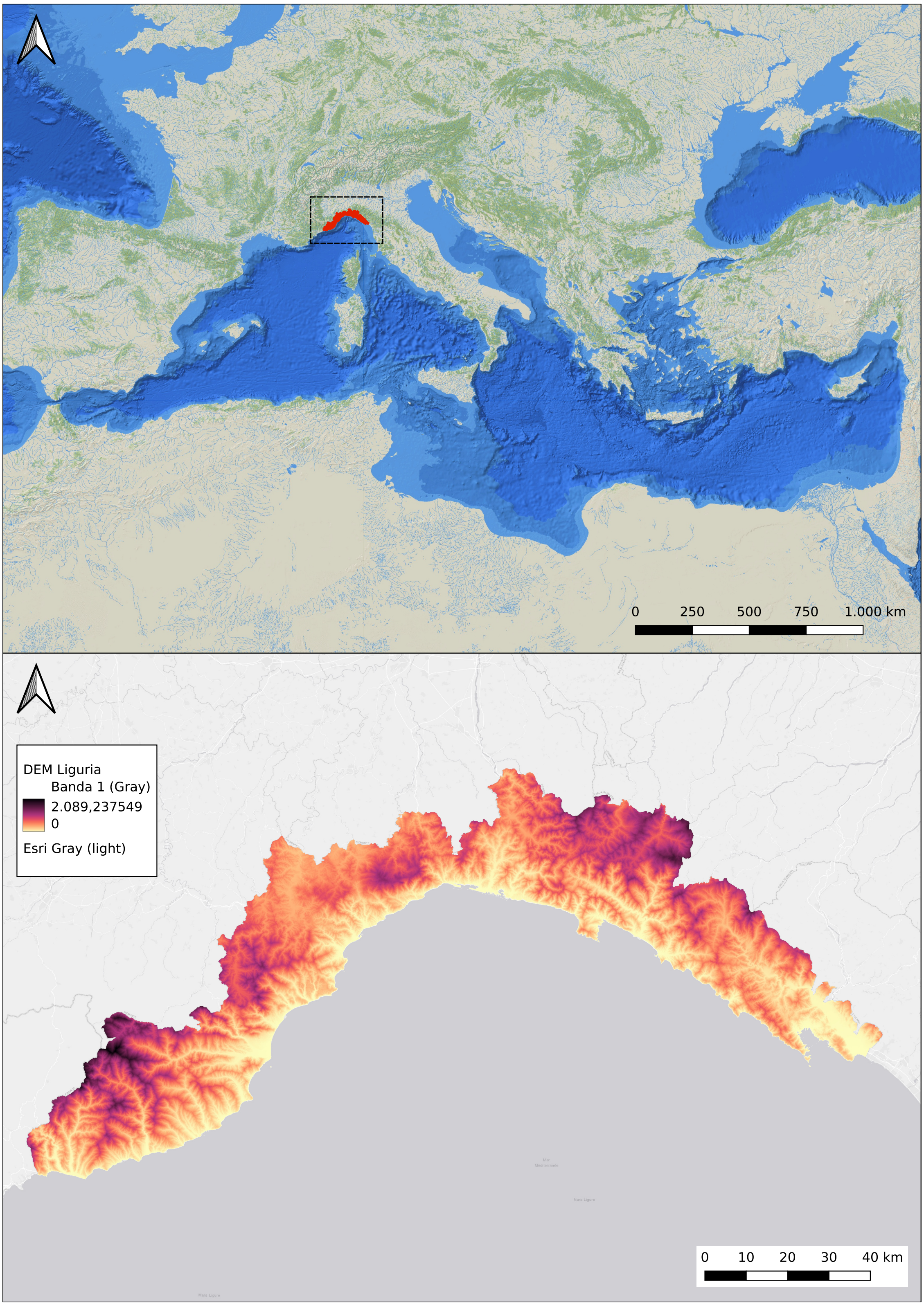

Fig. 1.1 Top panel: the location of the Liguria region (in red) within the Mediterranean Sea basin. Bottom panel: DEM of the region highlighting low-lying coastal portions in yellow and higher elevations in darker tones.

estuaries.
Precipitations are on average more abundant in the eastern side of the region, and the rainiest months of the year are September to November. By comparing precipitation data for the years 1981-2010 against the 1961-1990 period, it was observed that precipitation has increased in recent years, in terms of both total accumulated precipitation, number of consecutive rainy days in a year and of maximum daily precipitation registered on rainy days. The highest hazard of extreme precipitation events has been estimated for Province of Genoa, which covers approximately the central portion of the region [27]. According to estimates proposed in the *Piano nazionale di adattamento ai cambiamenti climatici*, the mean sea level in Ligurian coastal waters will likely increase by 8 cm in the period 2021-2050 under the RCP8.5 scenario [28].

The combination of local topography with high population density and severe soil sealing have led to the region being affected by pluvial, fluvial and coastal floods, both historically and with increasing frequency in recent times [29, 30]. As it pertains to pluvial and fluvial floods in the area, the regional topography and geomorphology and their interaction with water runoff and river discharges in the determination of floods and landslide hazards has been studied extensively [31]. Ligurian watersheds are numerous and fragmented (it has been estimated that 90% of them is smaller than 15 km^2 [32]); this regional peculiarity has been mirrored by the heterogeneity in the units of analysis that have been adopted in flood research in this study area. These range from individual [33, 34] to multiple watersheds [35, 29] to smaller areas such as urban districts depending on the focus of the analysis [36]. In **Paper III**, intermediate units of analysis were utilised, based on the *Ambiti di Bacino* and relative sub-units that are administrative in purpose but correspond closely to the location of physical watersheds, and to aggregates thereof for watersheds of very small dimensions located in close proximity to the coastline.
When it comes to sea-driven inundation, the relevance of marine storms for the study area is attested in historical records dating back to the 17th century [37]; moreover, extreme sea levels and strong winds associated with storms in the recent past (the most relevant of which dates to October 2018) have caused significant damage to some coastal infrastructure and ecosystems within the region [38–41]. Within this context, recent literature has also dealt with the characterisation of coastal geomorphology [42, 43], wave climate and coastal hydrodynamics for some specific

near-shore portions of the regional coastal waters [44–47].

Various methodological approaches have been utilised to assess the multiple components of vulnerability and risk for floods of different types in the area. Indicator-based methodologies for the assessment of – respectively – risk and resilience to flash floods and exposure to coastal flooding caused by extreme sea levels have been proposed by Quagliolo et al. [29] as well as in **Paper II**. These works contributed to the delineation of the scope of indicator-based methodologies for first-order assessments in the region and highlighting intra-regional variability in flood vulnerability. Silvestro et al. [33] utilised a combination of hydrological and hydraulic methods to reconstruct a past pluvial flood event and assess hazard scenarios and potential damage for different design storms and watershed characteristics. In a comprehensive study addressing several components of risk and including assessments of hazard, exposure, vulnerability and impacts, De Angeli et al. [48] analysed the risk of fluvial and coastal flooding for the same area, highlighting the importance of developing combined coastal-fluvial flooding assessment in the region.

1.5 Research Objectives

The complexity of coastal systems and the of interrelationships between their components are reflected in the numerousness and heterogeneity of the methodologies that have been developed for the evaluation of coastal vulnerability to floods.
Some of these methodologies provide an overarching view of the vulnerability in a given area by aggregating and summarising a variety of diverse data on the natural and socioeconomic elements of coastal systems. They are most fruitful when utilised as first-order appraisals for public information or to orient policy towards the most critical zones within a specific region in anticipation of future more in depth analyses. In some instances, the role of these methodologies in bridging the knowledge gap between science and practice has been misinterpreted [6] and stretched to the point of losing sight of their original meaning, of which information they can convey and of their proper use in the context of improving climate resilience.
Some other methodologies instead have a more specific focus on individual components of vulnerability. Their finer precision is usually closely associated to their

reduced applicability whenever resources are scarcer, or in contexts – such as emergency response – where time is a relevant constraint.
This dissertation aims at improving the delineation of the strengths and limitations of some of the methodologies used to assess vulnerability to rapid-onset coastal flooding, eventually contributing to the identification of opportunities for methodological improvement where possible. This dissertation further focuses on the mapping products associated to the diverse set of methodologies analysed, in consideration of their fundamental importance in conveying the results of the vulnerability assessments and informing both the perception of vulnerability and the decisions taken to address it.

This dissertation is built upon the results of three main articles which constitute the base of the research developed during the course of the PhD. With the aim of making explicit the methodological framework and the logical and consequential relationships among the three works, this dissertation begins by presenting and overview of the state of the art of the modelling and mapping methodologies utilised in literature for the assessment of vulnerability to rapid-onset flooding (specifically focusing on flooding caused by ESLs, see **Paper I**). It then proceeds with a focus on methodologies for the assessment of coastal vulnerability which can be used to synthetically estimate it by aggregating information on a diverse set of its individual components (of which **Paper II** represents an example). The third section of the dissertation is dedicated to methodologies aimed at assessing in a more precise manner a lower amount of components of vulnerability, with a specific focus on susceptibility (of which **Paper III** represents a data-driven application). Concluding remarks and a discussion of the results and implications of the research are presented in the final section of this dissertation.
The more specific research objectives addressed in the appended papers are as follows:

1. There is high uncertainty pertaining to the future evolution of ESLs in the Mediterranean sea basin, but climate variability is nonetheless crucial in the determination of vulnerability to coastal flooding. **Paper II** presents a case study on how to include climate scenarios within a comprehensive indicator-based assessment methodology, with the aim of assessing the sensitivity of

the method to variations in climate scenarios and the implications of using its results to inform policy.

2. The identification of the spatial extent which might be interested by flooding within a coastal region can be computationally expensive. Data-driven applications are currently being used in research to estimate some relevant factors related to the spatial development of floods with reduced computational requirements, but they are linked to the quality of training datasets. **Paper III** presents a data-driven flood susceptibility assessment for compound coastal flooding in Liguria, with the aim of testing the applicability of such an approach starting from modelled ground truth instead of observational datasets, as a testing ground for moving towards a surrogate modelling approach.

3. **Paper II** and **Paper III** focus on methodologies that lead to different types of spatial outputs and address the strengths and limitations of the different mapping applications.

1.6 Dissertation Outline

The remaining chapters of this dissertation are developed in parallel with the analyses advanced in the annexed scientific articles, in order to highlight how the original research undertaken fits within the broader state of the literature.
In addition to answering the research questions outlined in Section 1.5 above, this dissertation aims to elaborate on the methodological issues involved at different levels in the assessment of coastal flood vulnerability. In order to articulate the structure in an organised manner, each of the remaining chapters will be articulated around a series of foundational elements, namely:

1. The concept, i.e. a summary of the theoretical underpinning of the issue or specific vulnerability approach being addressed.

2. The methodology, i.e. more operational considerations relating to methodologies for putting the above theoretical concepts into practice.

3. Considerations on the type of spatial representation resulting from the respective methods analysed.

Chapter 2

Modelling and Mapping Applications for Rapid-Onset Coastal Flooding

2.1 Coastal Flood Risk Management

Several risk assessment frameworks specifically tailored to coastal areas have been developed in the last decades [49]. Hinkel and Klein [50] provided an overview of the evolution of methodologies for the assessment of coastal vulnerability to sea level rise (SLR). Their work was among the first to highlight the shortcomings of the early global vulnerability assessments, including matters related to the need to increase the spatial resolution of data, the limitations brought by considering mean SLR as the only driver of coastal vulnerability and the failure to account for the feedbacks and interactions between bio-geophysical and socio-economic dynamics. In their work, the authors proposed the Dynamic and Interactive Vulnerability Assessment (DIVA) tool, designed for the assessment of coastal vulnerability from subnational to global levels and aimed specifically at overcoming some of the aforementioned limitations. The DIVA approach focused on improving the integration between natural and social science knowledge in order to more accurately depict interactions between these two components, and to make such knowledge available to diverse types of end-users.

The necessity to consider both the bio-geophysical and socio-economic systems within coastal vulnerability assessment then became progressively well-established and integrated in subsequent frameworks proposed in literature. One such instance was proposed a few years after the DIVA tool by Torresan et al. [51]. In their work, the authors proposed a Regional Vulnerability Assessment (RVA) methodology to tailor the assessment on a site-specific level and thus assist coastal communities in the conversion of vulnerability assessments into action. The RVA is an indicator-based approach which provides a relative measure of vulnerability within the study area with the aim to highlight priority targets at higher levels of vulnerability and providing ranked information and the identification of coastline portions for which the vulnerability index is homogeneous.

As the development of coastal vulnerability assessment approaches progressed in literature, authors emphasized increasingly more the role of research outputs within decision support systems (DSS) linked to a series of coastal hazards. This focus was the centre upon which the the largest integrated project devoted entirely to coastal flood risk, the THESEUS project (i.e., *"Innovative coastal technologies for safer European coasts in a changing climate"*), was based [52, 53]. Zanuttigh et al. [53] highlighted the evolution of DSSs for coastal risk management proposed in literature, referring specifically to Geographic Information System (GIS)-based tools able to perform scenario construction and analysis. In this context, the role of spatialized information in support of decision making has been highlighted as crucial in literature. The DSS proposed in the context of the THESEUS project was based on a combination and integration of the three main types of DSSs proposed beforehand, namely the assessment of vulnerability to natural hazards and climate change, the prediction of coastal regions' response to climate change and the evaluation of management options for the optimal use of coastal resources in order to identify feasible measures and the coordination of stakeholders. One of the aims of the project and annexed DSS was to support decision-making through a balanced approach able to combine deterministic models and discussion-based assumptions based on expert opinions.
Van Dongeren et al. [1] proposed the EU-funded Resilience Increasing Strategies for Coasts - Tool Kit (RISC-KIT) project, pertaining specifically to low-frequency, high-impact events in coastal areas. The aim of the project was to optimise the mix of prevention, mitigation and preparedness (PMP) measures related to such hydro-meteorological events in a way which was specifically tailored to coastal areas, whereas previous frameworks for disaster risk reduction (DRR) such as the Sendai Framework for Disaster Risk Reduction [54] or the EU Floods Directive were not

specific for coastal hazards and tailored to coastal issues.

The different communication and analysis paradigms utilised by research and stakeholders, as well as the multifaceted interests playing a role within coastal planning require the management and integration of different needs and priorities. Failing to address these complex interrelations by adopting a conventional sectoral management has led in the past to coastal management issues [55]. For these reasons, broader coastal management paradigms were also proposed in literature, related not only to the management of hazards and planning for disaster PMP, but in general to provide a broader paradigm for the promotion of sustainable development in coastal zones.
The Integrated Coastal Zone Management (ICZM, sometimes also referred to as Integrated Coastal Management (ICZ) [56]) represents such a paradigm for a comprehensive coastal management process, encompassing *the full cycle of information collection, planning (in its broadest sense), decision making, management and monitoring of implementation* [57]. Within a study on the uptake and operationalisation of the ICZM framework in Europe, Shipman and Stojanovic [56] highlighted the fundamental role of informational obstacles between sectors at play in coastal areas, and between science and policymakers, as relevant obstacles for the ICZM. When it comes to the informational obstacles between science and policy, the most relevant concerns raised pertained to the discrepancy between the real needs of coastal communities and the data and research conducted [56]. These, in turn, were not strictly related to the technological means used to communicate and disseminate research results to a broader non-scientific public, but rather to obstacles in the creation of networked relationships and a tighter dialogue *between the research community and those with practical responsibilities for the coast* [56].

This overview highlighted the various complexities involved in managing the coastal zone as a whole, the management of climate risks in it, and finally the intricacies involved in communicating research results in such a manner that they can be used to their full capacity. When analysed in light of the rapid-onset coastal flooding processes that represent the focus of this work, facing these complexities requires firstly an effort towards the systematisation of the complex flooding processes affecting coastal zones. Section 2.2 highlights one of the most well-established frameworks for the schematisation of the coastal flood system proposed in literature.

This framework was utilised in **Paper I** annexed to this work to systematise the analysis of which instruments have been proposed in literature specifically with the purpose of supporting the preventive phase of the flood management process. Section 2.3 presents previous literature findings on this subjects and proposes an overview of the main results obtained.

2.2 The DSPRC Framework

The Driver-Source-Pathway-Receptor-Consequences (DSPRC) framework can be utilised to frame the coastal flood system by providing a lens through which its components can be subdivided, put into relation among each other and analysed. The framework was first formulated as Source-Pathway-Receptor (SPR) in the 1980s in the field of environmental pollution management by Holdgate [58]. It was then widely implemented in several different risk management fields, expanded and adopted at the institutional level to conceptualise and work with complex coastal systems [59]. In the EU, the framework - formulated as SPRC - was utilised as the main conceptual model at the base of the THESEUS project [52, 53].
Within the DSPRC conceptual model, flood systems are represented as a linear succession of their individual components and their causal linkages. When considering coastal flooding specifically, the driver is the underlying climate variability (natural and anthropogenic) resulting in spatially and temporally varying patterns that in turn have an effect on the magnitude and frequency of meteo-oceanic extreme events. The source can be understood as the main environmental hazard being generated, which for coastal flooding can be waves, storm surges, tides and mean sea levels. The pathway component represents *the mechanisms that convey flood waters that originate as extreme weather events to places where they may impact upon receptors* [60]; in the case of coastal flooding, pathways include coastal flood defence structures located at the water-land boundary. The inland systems affected by flood are the receptor, composed of both natural and built environments and inclusive of the people and infrastructure potentially affected. While the consequences are strictly related to the receptor, they can be more narrowly interpreted as estimates of the changes in individual socioeconomic variables brought by the effects of flooding (e.g., econometric estimates of damage).
The different modelling and mapping applications utilised in the broad field of

coastal flood risk and vulnerability assessments can adopt narrower or broader perspectives, and subsequently address distinctive subsets of the DSPRC framework components. In turn, narrower or broader perspectives and assessment methodologies and their associated mapping products can find application in different phases of the coastal flood risk management process, based on the different information needs and depending on locally-available resource and time constraints

2.3 Information Requirements for Flood Management

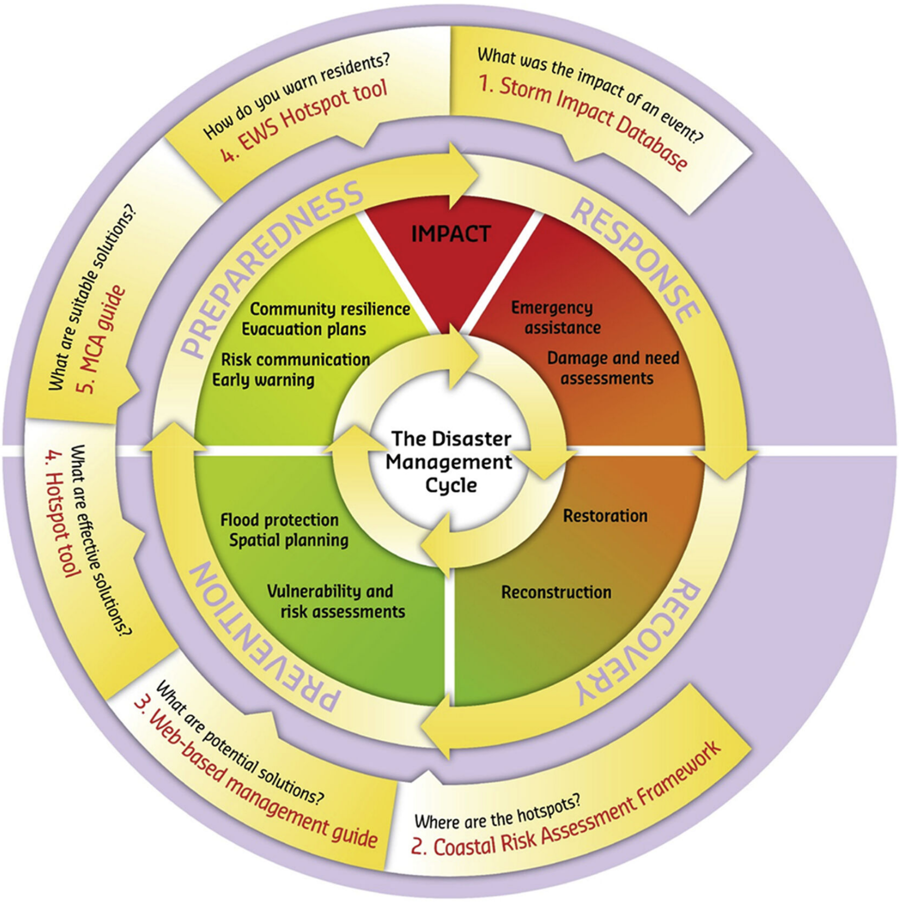

Fig. 2.1 The Disaster Management Cycle, describing the Response, Recovery, Prevention and Preparedness stages. Activities related to the cycle are also highlighted, along with the decision-support tools proposed in the context of the RISC-KIT project [1]. Reprinted from *Coastal Engineering*, Vol 134, article by van Dongeren et al. [1], with permission from Elsevier (license number: 5936531290362).

Within the paper presenting the RISC-KIT project, van Dongeren et al. [1] highlighted the different stages of the disaster management cycle – i.e., response, recovery, prevention and preparedness. The authors further identified some of the most important activities that are needed in the different phases of the cycle, to which a set of devised elements is associated (Figure 2.1). These measures are interdependent, as are the different phases of the disaster management process. The collection of a storm impact database during the disaster response phase is a fundamental step to support the following phases of the disaster management cycle. Spatial planning activities for flood protection are performed during the disaster prevention phase, which requires the deployment of vulnerability and risk assessments, including the identification of areas at increased risk (i.e., hotspots). After this stage, coastal managers might be interested in the identification of potentially available measures and in the assessment of their effectiveness. In order to select DRR strategies based on a set of potential solutions, the managers would also need to combine potentially conflicting interests and integrate different perspectives of end users and stakeholders in order to identify suitable solutions. The preparedness stage of the coastal risk management cycle, in turn, entails the conception of resilience and evacuation plans, as well as of effective strategies for risk communication. The establishment of early warning systems (EWS) is also a fundamental step for the preparedness phase, aimed at providing residents of coastal communities with information on hazards when these are impending.

2.4 The Role of Flood Modelling and Mapping

As emphasised above, vulnerability and risk assessments are fundamental to the disaster management cycle, especially the prevention phase. Providing spatialized information on floods is essential within this outlook, and considerable literature has been proposed to address this need. The role of publicly available flood maps is crucial for rasing risk awareness, and to inform spatial planning regulations [61].
A systematic scoping review of the state-of-the-art of literature on modelling and mapping rapid-onset coastal flooding is proposed in **Paper I**. The review combined a broad scope covering all the main methodologies utilised for coastal flood modelling with a focus on the spatial representation of flood, in order to highlight how different modelling methodologies and their corresponding map outputs are utilised

as decision support tools. A wide geographical scope was adopted in the review, by accounting for literature covering study areas worldwide and not just in the Mediterranean, in order to elicit a broad range of different coastal areas and policy needs.

The review confirmed the findings of extensive previous literature on the differential scopes of utilisation of different types of methodologies. Specifically, the scope of utilisation of simplified, non physically-based modelling methodologies such as those based on indicators was referred in reviewed literature as pertaining mostly to the preliminary phases of the flood risk prevention stages. During these stages, there might be a need for comprehensive, synthetic information to provide an overall picture of the situation and orient attention towards the most critical areas in future more in-depth analyses. On the other hand, numerical methodologies and more in-depth appraisals were aimed most commonly at more advanced analyses, in which a restricted subset of DSPRC components was analysed with a better level of detail, with the aim to obtain more specific information to inform coastal adaptation policies and the setup of flood preparedness strategies.

Focusing on the type of spatial representation of floods adopted in research allowed to complement previous literature on the lack of a shared common understanding about some of the foundational elements of flood management, such as the vulnerability and risk concepts and their components. Such research shortcomings were indeed reflected in the flood maps proposed in reviewed literature, whereby no shared practices about the which elements to represent and how to depict them could be drawn. Even though it must be acknowledged that vulnerability is context-specific and therefore its assessment might vary considerably, such a lack of shared best practices is likely to result in difficulties in communicating research findings effectively, and to transform them into actionable information.
Focusing on the spatial representation of floods is furthermore crucial because flood maps can aid in bringing flood risk perception closer to reality. As highlighted by some literature contributions examined in **Paper I**, taking into account the cognitive components of risk is fundamental, as research has shown most individuals to have a skewed risk perception. Specifically, Bruno et al. [49] highlighted the importance of integrating physical risk with the social perception in order to attain more effective management, as perception plays a key role in risk management. Coquet et al. [62] and Elineau et al. [63] utilised sketch maps produced by individuals in coastal areas

and compared them with objective measure of risk. Both studies concluded that there was a skewed perception in all cases. When referring to the perception of individuals who have a practical role and decision making responsibilities in coastal management, these findings further corroborate the need of providing decision makers with information on coastal flood risk that is both accurate and easy to understand and translate into action.

Chapter 3

A Comprehensive Approach to Coastal Vulnerability

3.1 Theoretical Foundations of Vulnerability Indicators

Indicator-based vulnerability assessment (henceforth, IBVA) methodologies are one of the possible approaches which can be utilised for the operationalisation of the concept of vulnerability in the context of CCVA (see Chapter 1). Indicators are functions that map observable variables (i.e., indicating variables) to theoretical variables or concepts [7], and are most commonly expressed in their simplest form as scalar indicators. Indicators are often linear, and should always be monotonously increasing or decreasing, as non-monotonous functions would be misleading [6].

IBVAs stand out within the broader spectrum of CCVA methodologies for their particularly prominent purpose of supporting policy decision. As such, they tend to be targeted specifically at audiences composed of policymakers and practitioners, and are commonly developed and communicated also outside of scientific journals [9].

Their role at the interface between research and policy has caused IBVAs to elicit mixed responses from the policy and research communities. While increasing demands for the development of IBVAs come from the former because of their synthesis potential, growing concerns and criticisms have come from the second. Hinkel [6] identified this misfit to come from a twofold confusion pertaining to *what vulnera-*

bility indicators are and which arguments are available for building them on one side, and to *the kinds of policy problems to be solved by means of indicators* on the other. In the same study, the fundamental arguments for the development of vulnerability indicators are also highlighted, including: i) deductive arguments based on theory, ii) inductive arguments based on data pertaining to the indicating variables and observed harm, iii) normative arguments based on value judgements.

The significant sources of uncertainty associated with incomplete knowledge of the relevant climatic processes and the interactions that occur in complex SESs can lead to substantial limitations in methodologies that aim to synthesise such unknown or highly uncertain processes. This problem is particularly relevant for IBVA methodologies, in which epistemic uncertainty is associated to the processes generating vulnerability, and most significantly to the quantification of the relationship between SES elements with vulnerability [10].
For these reasons, Hinkel [6] highlighted the need to re-identify the boundaries of IBVAs with respect to those that are currently cited in literature (scope, types of systems addressed, types of questions answered), working towards a re-evaluation of whether vulnerability indicators are *fit-for-purpose*. The study identified six different types of problems that literature indicates may be addressed by vulnerability indicators, including i) the identification of mitigation targets; the ii) identification of vulnerable people, communities, regions, etc.; iii) raising awareness; iv) the allocation of adaptation funds; v) monitoring of adaptation policy; and vi) conducting scientific research. Hinkel [6] found that for all such aims except for the second, vulnerability indicators were unsuitable, either because vulnerability was not the right lens through which to address the research problem or because indicators were not the adequate methodology. Furthermore, when referring to the second type of problem (i.e., the identification of vulnerable people, communities, regions), it was possible to address it through vulnerability indicators provided that further considerations on the scientific delimitation of the problem were carried out.
From this theoretical overview it becomes evident that IBVA methodologies are widely used. However, more care needs to be taken when developing them and also when applying existing methodologies to individual case study contexts.

3.2 Indicator-Based Vulnerability Assessment Methodologies

Even though the breakdown of complex systems into individual components has been criticised as reductionist, relevant literature has highlighted that if done properly, it can allow gaining more in-depth knowledge about the interactions happening at the base of the systems themselves [9].
Two main approaches to the selection of vulnerability indicators have been identified in literature, namely the deductive approach and the inductive approach [9]. In the former approach, a theoretical framework on the relationships governing the functioning of a systems must be set up, and the selection of indicators must be formulated in a way that mirrors such relationships. One further step in the deductive approach might be that of selecting which among the system-governing relationships to keep for a more or less simplified representation. On the other hand, the inductive approach to the selection of indicators calls for relating a given measure of vulnerability to a large number of indicators and proceed to the selection of the latter based on measures of the statistical significance of the relationship between vulnerability measures and indicators. While a deductive approach involves an theoretical investigation about how the system works, the inductive approach relies on the empirical generalisation of the identified relationships. Patterns repeating throughout a significant number of systems can in turn be used in later stages to build theoretical formulations about the functioning of a system [9].
A point linked to that of the formulation of a theoretical model at the base of the deductive approach was raised by Hinkel [6], who emphasised that the necessity of building a predictive system at the base of vulnerability assessment is rooted in the forward-looking aspect of vulnerability, requiring a function to be established between a present condition and a future state (see Chapter 1). At the same time, indicator-based approaches are by definition simple and time-independent; these two aspects qualify as significant impairments in the utilisation of IBVA methodologies, as they usually do not contain time as an argument.

Three main steps have been identified as involved in the development of IBVAs [6, 10], as follows:

1. The first step consists in the identification of what it is to be indicated, by answering questions pertaining to which SES is the object of the study, which attributes of the SES are to be referred to (e.g., the vulnerability of biological productivity, of the biodiversity or similar), and which climate-related stressors are to be considered.

2. The second step pertains to the selection of indicating variables, based on the answers given during the previous step and on considerations on the level of detail and comprehensiveness in the representation of the system variables and dynamics to be achieved.

3. The third step is the aggregation of individual indicators into a composite measure (i.e. an index, sometimes also called composite indicator), which can be done at different levels of complexity, depending on whether a simple mapping between a given combination of indicators and a given vulnerability level is considered, or whether appropriate aggregation procedures are used.

Aggregation is not considered necessary, and it should be regarded as *an alternative to mechanistic modelling in the case when the latter is not possible* [10]. Aggregation procedures are based on assumptions about the degree of substitution or compensation between indicators. Several aggregation and normalisation methods for indicators have been utilised in literature based on the underlying assumption behind the relationships governing the different system components [10].

The main methodological shortcomings linked to the development of indicators highlighted in literature can be expressed at different levels of detail. On a general note, according to Eriksen and Kelly [9], the robustness and relevance of indicators has been severely hampered for a long time by the lack of clear theoretical and conceptual frameworks for the selection of indicators, which are often not stated clearly in studies, hinting at the theoretical and methodological confusion at the base of the study. On a more specific level, significant theoretical and methodological limitations exist pertaining to the uncertainty, robustness and possibility to verify vulnerability indicators. Considerations on uncertainty are linked to the significant random and nonrandom indicator fluctuations caused mostly by the aggregation procedures – in both time and space – and to the subjectivity playing a role in indicator weighting [10].

Fernandez et al. [64] conducted a study on the effects of utilising different aggregation procedures for indicators, based on the utilisation of a *Constant Elasticity Substitution (CES) function where the parameter of interest is the elasticity of substitution between indicators*, that is, the degree to which one indicator can substitute or compensate another in the composition of an overall index/composite indicator. The authors analysed the robustness of indicators based on the vulnerability indicator values corresponding to different aggregating procedures. The study concluded that IBVA methodologies are not robust, as their results do not hold under different values of elasticity, even when referring to the same population groups and climate hazards. This fact has in turn significant implications in terms of the usability of such methodologies to provide vulnerability rankings and eventually inform policy unambiguously, eventually resulting in the inability to set action priority and attain coset-effective climate planning.

Other considerations about the limitations of IBVAs can be made with respect to the spatial scale of aggregation. For the social vulnerability component specifically, the national level has long been considered and utilised as the relevant unit of spatial aggregation, as most relevant data is collected and processed at that level. Though, issues pertaining to such a choice are highlighted when considering that the scale at which the effects of climate change are usually suffered is commonly smaller than the national one, and that vulnerability patterns might be strongly differential within a national territory, raising scale issues [9].

Even within the boundaries defined by their limitations, IBVA methodologies can still find application to support climate-related policy-making, provided that the *one-size-fits-all* vulnerability assessment label should be problematised, and that the scope of application of indicators should be better defined [6].

3.3 Indicators of Vulnerability to Coastal Flooding

Thus far, this Chapter proposed an overview of the methodological foundations at the base of IBVA approaches. It highlighted the main milestones related to their development, and discussed the main limitations, adopting a generic outlook pertaining to vulnerability indicators. In this section, the focus of the analysis will be shifted towards indicators of flood vulnerability, of which one instance was utilised for the development of the case study presented in **Paper II**.

The state-of-the-art of indicator-based methodologies for coastal flooding was assessed in **Paper I**. The systematic review protocol adopted in the work allowed to highlight the main recurring points about the utilisation of such methodologies within research on coastal flooding, as follows:

1. Indicator and index-based methodologies were most often utilised in studies proposing comprehensive assessments of vulnerability and risk to coastal flooding.
2. On a related note, study authors usually identified the role of the proposed index-based assessment as being able to obtain first-order appraisals, in line with the recommendation by Hinkel [6] stating that IBVAs *should only serve as high-level entry points to further more detailed information behind*.
3. The Coastal Vulnerability Index (CVI) [65, 66] represented the most prevalent instance of this class of methodologies among reviewed literature.
4. GIS-based Multi Criteria Decision Analysis (MCDA) was commonly utilised to choose indicators to include and their weights to compute the aggregate index.
5. The most relevant limitations emphasised in literature referred to the simultaneous integration of the natural and socioeconomic components. This in turn resulted in inconsistencies in the spatial representation the index in flood-related maps (see Section 3.4).

A case study analysis of coastal vulnerability to flooding through an indicator-based assessment methodology was developed in **Paper II**. In the paper, the InVEST Coastal Vulnerability model [67] was used to obtain a version of the widely-utilised CVI in a spatially-explicit manner for a wide portion of the Ligurian coastline. The model takes a series of pre-processed vector data layers pertaining to relevant bio-geophysical variables and then proceeds to compute the index for a series of evenly-spaced points located along the shoreline of the area of interest. The model accounts for the spatial interpolation of the vulnerability-determining inputs towards

the shoreline points in an automatic fashion.
At the beginning of the study design, the main objective of the study was to assess the scope for considering climate variation within the approach, as the methodology required the inclusion of climate-related data pertaining to wind and waves to compute one of the relevant the sub-indicators considered. Two representative 30-year climate periods were input in different model runs, and the resulting model outputs were compared. The analysis of results allowed to ascertain that such an approach – and namely the index aggregation procedure – masked most of the variation observed between the two climate periods considered.

These results can be interpreted within the broader theoretical discussion explored above in this Chapter and in Chapter 1 pertaining to the operationalisation of vulnerability, insofar as vulnerability can be understood as a comparison either through time or in space. Concerning time, not only IBVA methodologies do not consider time within them – as extensive theoretical research has shown –, but variations in time are not even captured when comparing different realisations of the same indicators run with different input data. This excludes any diachronic use of such methodologies, and might hinder the role of such assessment in providing continued support through time to the implementation of coastal adaptation policies aimed at increasing climate resilience.
With regards to space, the methodology adopted in **Paper II** was characterised by relevant limitations of the type of spatial representation the output was provided in, which are explored in more detail in Section 3.4 below.
The research carried out in the context of **Paper II** allowed to further corroborate some of the theoretical discussion developed above in this dissertation pertaining to the difficulties in defining the boundaries of which SES elements are being addressed. Namely, in the context of the CVI, the vulnerability to flooding is usually analysed in conjunction with vulnerability linked to erosion processes. In turn, most studies jointly consider the two independently of the relevance of erosion processes for the coastal area of interest, and fail to explicitly address the mismatch between the applicability of the methodology and the underlying elements of the SES that the analysis is focusing on.

3.4 Spatial Representation of Indicators of Coastal Vulnerability

Issues of geographical scale and of spatial representation of vulnerability have been addressed extensively in literature. As noted by Ran et al. [68], such a focus on the spatial representation of vulnerability is closely linked to the utilisation of vulnerability assessments for policy or practice envisioned by researchers, though the actual uptake of such assessments by practitioners remains an open question.
Even if previous research highlighted that most vulnerability studies are carried out at higher levels (e.g., regional, national), IBVAs are most fruitfully developed at the local scale because at that level *it is easier to define systems, identify socioeconomic and biophysical processes that determine vulnerability and build inductive arguments to characterize them* [10]. The adoption of a small spatial scale might also help alleviate some of the distortions caused by aggregation typical of national-level appraisals, as highlighted by Eriksen and Kelly [9].

In **Paper I**, a focus was devoted to the characterisation of the spatial representation of rapid-onset coastal flooding in literature. The systematic study design allows for two possible perspectives on the literature reviewed, depending on whether it is considered through the lens of the type of flood map on the one hand, or from the perspective of the type of methodology used on the other.
The former is adopted explicitly within the article, and can be summarised based on the following points:

1. With regards to vulnerability to rapid-onset coastal flooding, reviewed literature adopted a broad spectrum of interpretations, from articles focusing exclusively on biophysical vulnerability, to those considering a mix of the two components, to those considering exclusively socioeconomic vulnerability.
2. As a result, the spatial representation of vulnerability was dependent on the physical distribution of the geographical element under consideration and the data aggregation strategy adopted by the individual study, with the result being miscellaneous levels of adherence to the distribution of natural factors.
3. Nevertheless, the spatial representation of vulnerability as being referred to purely administrative units was overall prevalent.

Most of these results still hold when adopting the perspective of the type of spatial representation presented in studies adopting indicator-based methodologies, since those studies are most commonly flood vulnerability – or to a lesser extent risk – assessments. Within this context, it is noteworthy that the type of spatial representation of the CVI obtained in the context of **Paper II** seems to represent a relatively rare example, and that some of the limitations related to it and discussed in the article (i.e., points located arbitrarily along the shoreline without any reference to the physical processes of flooding that shape vulnerability, and lack of information on inland portions of the coastal study area) might not necessarily hold in general for index-based coastal flood vulnerability assessments.

Nevertheless, such shortcomings informed the choice of which methodology to address in the following phases of the research, which represents the topic addressed in Chapter 4.

Chapter 4

Assessing Susceptibility to Coastal Flooding

4.1 Susceptibility to Flooding

Susceptibility can be defined as the physical predisposition of a system to be negatively affected by a dangerous phenomenon and suffer its consequences due to its intrinsic characteristics [25, 69, 26]. Flood susceptibility assessments aim at identifying areas characterised by topographic, land cover or geomorphological characteristics that are most determinant to the accumulation of water. Flood susceptibility assessments are essential tools to inform disaster prevention strategies and flood preparedness, and can be carried out through a wide variety of methodologies spanning from multi-criteria to statistical and data-driven methods [70].

4.2 Data-Driven Flood Modelling and Mapping

The systematic literature review carried out in the context of **Paper I** allowed to highlight how data-driven methodologies are used in several different ways to model and map rapid-onset coastal flooding, as well as for the estimation of other relevant DSPRC components of the coastal flood system (see Section 2.2).
Some relevant examples include:

1. Data-driven models can be utilised as surrogates for high-fidelity physics-based models for ocean circulation and wave modelling, since their reduced computational resource requirements and shorter runtimes make them more suitable in contexts where there might be resource or time constraints. These data-driven surrogate models are generally aimed at modelling water dynamics just until the shoreline demarcation.

2. Machine Learning (ML) models can also be utilised for the simulation of the propagation of coastal floods inland. Current research efforts in this field are aimed at improving upon the usual representation of surrogate models which neglect that inputs are time series and outputs are floods that propagate inland. One such instance was proposed by López-Lopera et al. [71], where a multioutput Gaussian process based model was developed which can be used with time-varying inputs and to provide information on spatially-varying inland coastal flooding.

3. Data-driven flood susceptibility assessments, to which Section 4.3 is dedicated.

4. Additionally, data-driven methods can also be utilised to obtain post-event flood inundation maps, which were not addressed in the context of **Paper I**. ML can in that context aid in bypassing some of the problems commonly linked to the visualisation of water in remote sensing applications, such as cloud cover during storms in the case of optical imagery or other types of distortions in radar imagery [72]. Remote sensing techniques such as change detection are commonly used to obtain flood inundation maps, by comparing pre-event and post-event images to distinguish between flooded and non-flooded areas. Flood inundation maps are most commonly used for emergency response and damage assessment after the event has occurred, but can can also represent essential tools providing *ground truth* data within a supervised ML perspective.

4.3 Data-Driven Flood Susceptibility Assessment

Data-driven flood susceptibility assessments are usually configured as pixel-wise supervised learning tasks, in which a series of static predictors is stacked and utilised in conjunction with ground truth data on the location of past flood events in the area to predict susceptibility to floods. Because of the non-diachronic nature of most susceptibility analyses, the predictors are generally considered to be static within the time horizon adopted for the assessment, and can be influential for both marine-driven flooding and flooding of different sources.

Most of the data-driven flood susceptibility assessments reviewed for **Paper I** utilised exclusively static predictors, and a limited proportion also included some climate-related predictors. In the case of pluvial and fluvial flood susceptibility, the inclusion of climate-related variables can be more straightforward because of the possibility of representing precipitation datasets in a two-dimensional way, while the same is not always feasible for climate data related to the generation of marine-driven flooding.

The availability of extensive data on the location and extent of previous flood events in the study area is usually considered to be an essential pre-condition for the development of data-driven flood susceptibility assessments. Though, it represents at the same time a strict constraint, insofar as such data are expensive to retrieve *in situ* and can be difficult to obtain through Earth observation.

Most data-driven approaches to flood susceptibility assessment utilise observational datasets on the location of past flooded areas as the ground truth for model training [73–79]. Section 4.3.1 below reports the analyses carried out to investigate the possibility to obtain observed post-event flood extent data to utilise as ground truth in the case study developed for **Paper III**. As the amount and quality of data were not sufficient for use in a data-driven application, the study was subsequently rerouted towards the use of modelled ground truth, as described in more detail in Section 4.4.

4.3.1 Availability of Observational Coastal Flood Data

Assessing flood exposure in urbanised coastal environments ideally entails attaining a sufficient level of detail to discern among different portions of the coastal and urban infrastructure that might be affected by extreme sea-level changes. Some remote sensing-derived databases of low-resolution flood inundation maps exist, such as the one curated by the Dartmouth Flood Observatory (DFO) (based on twice-daily imaging of Terra-MODIS and Aqua-MODIS at 250 m spatial resolution) or the MODIS Near Real-Time Global Flood Product (same source and final product resolution). Though, due to the intrinsic nature of rapid-onset flooding events combined with the inverse relationship between satellite revisit time and spatial resolution, a scarcity of flood inundation maps at sufficiently high resolution exists for coastal applications. In Europe, the 2010 storm Xynthia is usually considered the only (recent) sufficiently

documented large-scale coastal flooding event in Europe [80] to allow estimation of relevant flood variables including flooded area extent. Other literature has proposed and tried using proxy data to measure the post-coastal flood event inundated area – for instance, Gallien et al. [81] used satellite data to identify wrack lines a few days after the flood event and used those as markers of the flooded area extent.
Non-comprehensive flood inundation maps at higher resolution exist as well, such as those produced in the context of the Copernicus Emergency Management Service (CEMS), whose activation is requested by authorised members when necessary. Though, the irregular coverage of such data is a significant hindrance when compared to the training data requirements of supervised ML applications. The near-real time Global Flood Monitoring (GFM) service represents another option for the derivation of observational flood ground truth data. The GFM is developed in the context of the Global Flood Awareness System (GloFAS) as part of the CEMS. The service is aimed at providing a continuous stream of flood monitoring data products, which are obtained by processing in a systematic way all incoming Copernicus Sentinel-1 Synthetic Aperture Radar (SAR) data and applying three state-of-the-art flood mapping algorithms. Since the GFM service was made operational in 2021, no such data exists for the 2018 marine-driven flood event utilised as an example in the study area.

In the area of interest of **Paper III**, some data on the location of flooded area derived from post-event *in-situ* measurements provided by the local watershed administrations exist for pluvial and fluvial flooding events [82]. Though, no records of predominantly sea-driven flooding extent exists for the area.
A series of analyses was carried out within this context in order to test the retrieval of flooded area extents for sea-driven coastal flooding in the area for a known coastal flooding event. Between October 29th and 30th, 2018 a storm surge in the context of Storm Adrian (*Tempesta Vaia*) led to the flooding of significant portions of the seafront and to the destruction of the Carlo Riva Port in the city of Rapallo, Liguria. A multisource flood mapping approach based on the work of Hamidi et al. [83] was attempted for this event, in which a series of SAR change detection-based flood indices is computed and validated by comparison with an optical-based flood index (e.g. the Modified Normalized Difference Water Index, MNDWI [84]) [85]. The available optical and SAR pre- and post-flood event images are summarised in Table 4.1.

Satellite	Date (dd/mm/yyyy)	Status	Orbit-Polarization	Resolution
Sentinel-1B	21/08/2018	Before flood	Ascending - VH	10 m
Sentinel-1A	22/08/2018	Before flood	Ascending - VH	10 m
Sentinel-1A	27/08/2018	Before flood	Ascending - VH	10 m
Sentinel-1B	01/11/2018	After flood	Ascending - VH	10 m
Sentinel-1A	02/11/2018	After flood	Ascending - VH	10 m
Sentinel-2A	19/10/2018	Before flood	–	20 m
Sentinel-2B	03/11/2018	After flood	–	20 m

Table 4.1 Available satellite data for flooding event on October 29th, 2018 in Rapallo.

A variety of SAR-derived flood indices based on the comparison of pre- and post-flood event image stack backscatter coefficients have been proposed in literature. The following three were utilised for this analysis.
The Ratio Index (RI). Originally proposed by Vanama et al. [86], it is represented by the following equation:

$$RI = \frac{|min(\sigma_{0[AF]})|}{|mean(\sigma_{0[BF]})|} \tag{4.1}$$

The Difference Image Index (DII). Originally proposed by Long et al. [87] as the absolute difference between pre- and post-flood event images and adapted for multitemporal image stacks in [83, 88] as represented by the following equation:

$$DII = |min(\sigma_{0[AF]})| - |mean(\sigma_{0[BF]})| \tag{4.2}$$

The Normalised Difference Flood Index (NDFI) [89] is represented by the following equation:

$$NDFI = \frac{|mean(\sigma_{0[BF]})| - |min(\sigma_{0[AF]})|}{|mean(\sigma_{0[BF]})| + |min(\sigma_{0[AF]})|} \tag{4.3}$$

In all the formulas presented above, $\sigma_{0[BF]}$ and $\sigma_{0[AF]}$ represent respectively the backscatter coefficient of SAR imagery before and after flood. All preprocessing for SAR data and SAR index computation was carried out in Google Earth Engine (GEE).
As it often happens for optical post-event flood images taken close to the event, in this case optical flood imagery was not suitable for flood mapping because of persisting storminess conditions. Extensive clouds over the study area lead to null image coverage after masking for both clouds and cloud shadows. The unsuitability

of optical data for the study was further confirmed by running an image segmentation algorithm for flood identification trained on optical imagery on the post-event flood image of November 3rd, 2018 [2, 3]. As shown in Figure 4.1, clouds and storminess conditions cause reduced visibility on the ground as well as leading to wrong classification of the land-water interface in the study area.

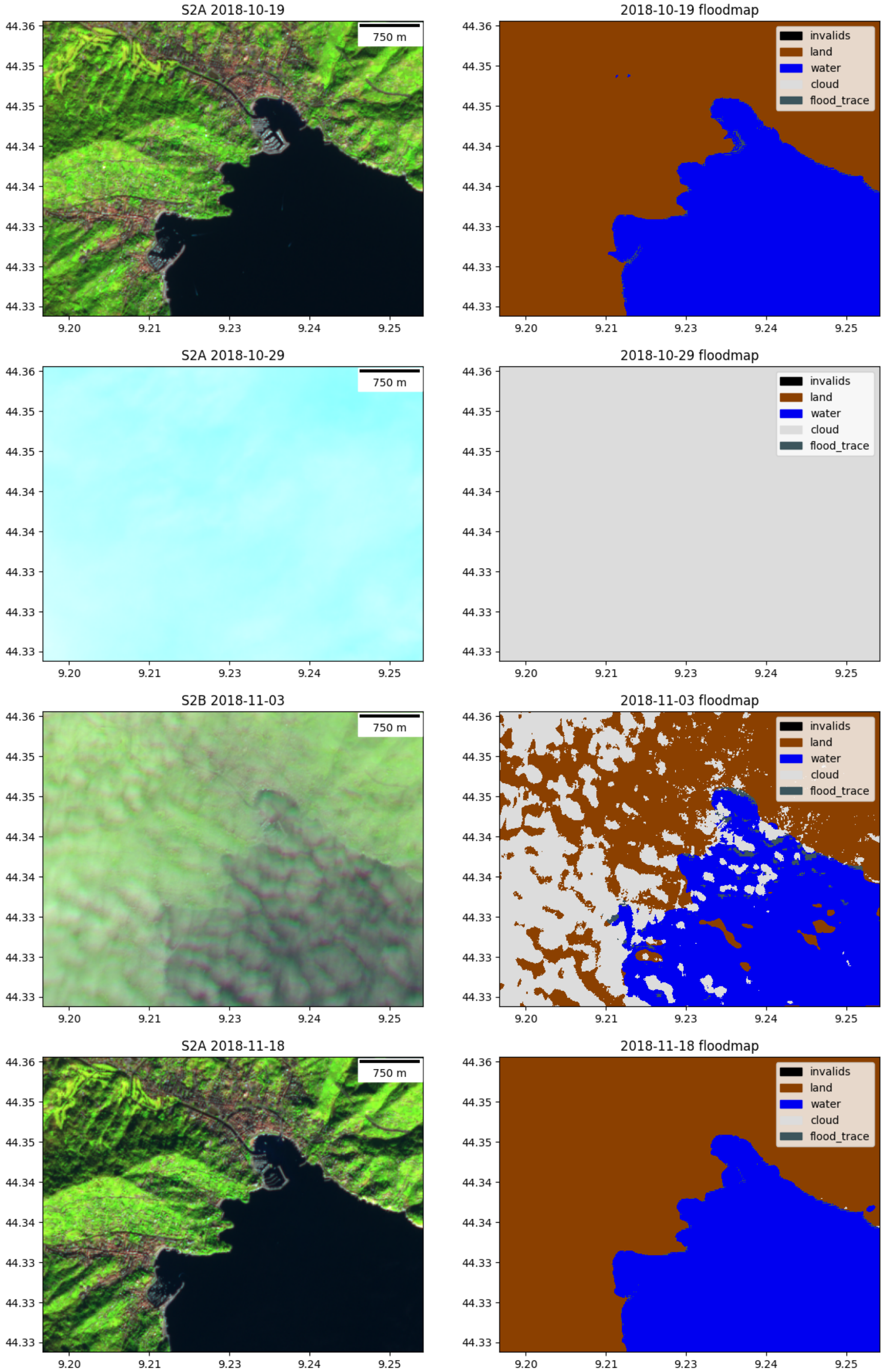

Fig. 4.1 Pre- and post-flood event optical imagery (Sentinel-2) for the coastal flood event of October 29th, 2018 in Rapallo. RGB colour composite images are presented in the left column. The right column represents the output of an image segmentation algorithm for flood identification trained on optical imagery [2, 3].

Flooded area delineation with the SAR indices presented above implies a thresholding procedure in which pixels above or below a certain threshold of the index distribution are considered as flooded. The threshold can be expressed by the following equation:

$$Threshold = mean(SAR\,Index\,Image) \pm k_f \times stdev(SAR\,Index\,Image) \tag{4.4}$$

Where the k_f coefficient represents the number of standard deviations from the mean above (for Ri and DII) or below (for NDFI) which pixels will be considered as flooded. A default value of k_f = 1.5 can be used for all three indices considered [83], but research has shown the coefficient to be strongly area-dependent and needing local calibration.

As a result of the aforementioned impossibility to validate the SAR-derived flooded area with MNDWI, an iterative approach was utilised to derive *robust* thresholds for the three indices, as summarised in Figure 4.2. The k_f coefficient was modified between 0.0 and 2.0 at 0.1 intervals for each index and flood maps were obtained for each threshold-index pair. The agreement (i.e., the number of pixels) among the flooded areas as identified by the three indices was calculated at every threshold level possible. The thresholds which guaranteed the maximum agreement among the flooded areas were chosen, subject to the percentage of flooded area in the image not exceeding that identified by thresholding with the default k_f coefficient values. A permanent water mask [90] and a maximum slope mask based on the Copernicus DEM GLO-30 dataset available in GEE (slope below 5%) were also utilised in the procedure to exclude permanent water bodies and steep areas not subject to flooding. Figure 4.3 shows the three indices utilised along with flooded areas identified thresholding with default and robust coefficients.

It is noteworthy that the Carlo Riva port of Rapallo which was flooded and suffered significant damage after the storm event was identified as being flooded across all indices even with default thresholding coefficients (cf. Figure 4.3). Though it is evident that the robust thresholds yield more coherent results in the identification of flooded areas also further away from the portal area, no further rigorous validation could be carried out due to data limitations in this specific case.

In addition, the identified flooded areas were of limited size and therefore this data did not represent a feasible option to be used as ground truth in the analysis.

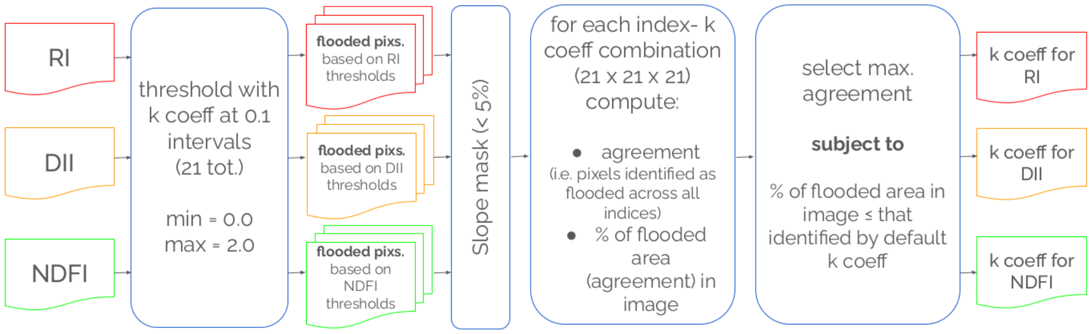

Fig. 4.2 Workflow adopted to identify robust SAR imagery index thresholding coefficients for flood identification in the study area.

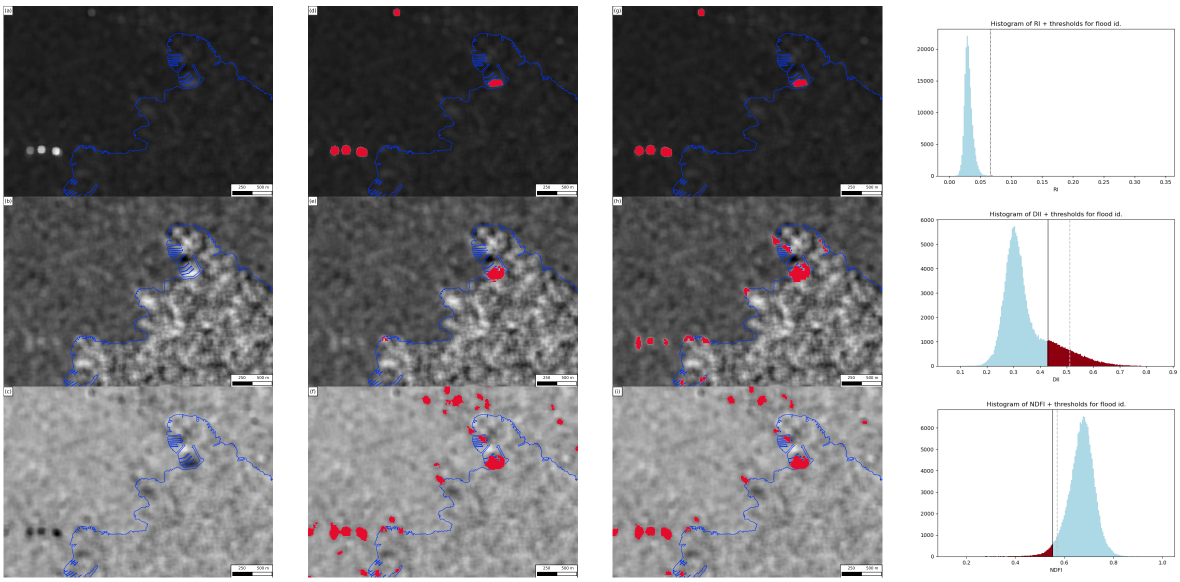

Fig. 4.3 Ratio Index (RI) **(a)**, Difference Image Index (DII) **(b)** and Normalised Difference Flood Index (NDFI) **(c)** for the coastal flood event of October 29th, 2018 in Rapallo. Figures **(d)**, **(e)** and **(f)** represent flooded areas identified by thresholding with the default coefficient. Figures **(g)**, **(h)** and **(i)** represent flooded areas identified by thresholding with the robust coefficients. The leftmost column represents histograms of the distribution of the three indices along with default (grey dashed line) and robust (black solid line) thresholds.

4.4 De-coupling Susceptibility from Observations: Towards Surrogate Modelling

In **Paper III**, the outputs of numerical flood modelling produced in the context of the European Floods Directive were utilised as ground truth for the supervised classification task, instead of observations. Similar approaches exist in literature [91–96]. Using modelled ground truth for flood susceptibility assessment means adopting an approach that is more akin to surrogate modelling than the usual flood susceptibility analyses presented in the literature. The objective of this approach was to test the efficacy of a relatively straightforward method to be used in a surrogate-like manner to reproduce the potential flood extent obtained with more complex methodologies, rather than to obtain new information about flood susceptibility in Liguria specifically.

Surrogate models can be characterised by high uncertainties in model outputs coming from different sources. In **Paper III**, the ground truth utilised was characterised by high levels of uncertainty and inconsistencies across the study area considered, as the original numerical models were often run separately for different portions of the coast, return times were set differently for coastal and inland flood drivers, and a simple planar projection approach was utilised to identify the coastal floodplain based on the water level modelled at the shoreline (see section on limitations of planar projection inundation models in **Paper I**).

Despite the limitations just mentioned, **Paper III** demonstrated that a relatively straightforward data-driven approach can be effectively used in a surrogate-like fashion for the comprehensive identification of areas susceptible to compound flooding in coastal areas with similar topography to the one considered. The use of modelled ground truth introduced less spatial bias in the analysis, and allowed to verify the classification results obtained, eventually moving towards the decoupling of the susceptibility assessment from the necessity of extensive observational records on previous hazardous events in the area.

4.5 Spatial Representation of Floods within Susceptibility Assessments

Published articles proposing data-driven flood susceptibility assessments usually follow a recurring structure involving the presentation of available training data (ground truth), the presentation of the flood influencing factors to use at predictors, the presentation of methodology and the resulting flood susceptibility maps.

The relevant characteristics of coastal flood susceptibility maps are discussed in detail in **Paper I**. In some of the articles analysed for the literature review, flood susceptibility maps were included in indicator-based vulnerability or risk analyses as part of the sensitivity or hazard components – in line with the terminological and methodological confusion associated to these concepts [97, 98].

The type of spatial representation of floods obtained in **Paper III** constitutes a significant improvement when compared with the results of **Paper II**, in terms of both the spatial continuity and as they also provide information for the inland portions of coastal areas. In **Paper III**, several spatial aggregation approaches were adopted, including utilising the individual watershed level as the base for the development of classification models. The results of the study allowed to gather geographically relevant information about the features of individual watersheds that might make data-driven approaches such as those explored in the analysis more or less suitable to identify areas susceptible to flooding based on topographic predictors.

Chapter 5

Discussion and Conclusions

This dissertation examined various methodologies used in coastal flood vulnerability assessment, assessing their scope of use within a broader literature context and developing some of their more specific aspects through case study articles.
The first chapter of the thesis dealt with some foundational and high-level elements of vulnerability that are essential for the theoretical framework of the rest of the topics covered. The reasoning behind the choice of the Mediterranean and the peculiarities of its coastal areas where examined therein. Finally, the research objectives were laid out.
The second chapter of the thesis addressed more specific aspects, shifting the focus from climate change vulnerability analysis in general to coastal flood vulnerability analysis in particular. It also presented the topic from a decision support perspective, highlighting the different types of analysis that can support the individual stages of the disaster management process. A systematic literature review on modelling and mapping methodologies for rapid-onset coastal flooding was proposed in **Paper I**. By combining a wide methodological scope covering all the main methodologies utilised for flood modelling in coastal areas with a focus on the spatial representation of flooding proposed in literature, the study provided a robust framework within which to place the more specific methodologies addressed in the remainder of the research.
The third chapter of the thesis dealt with indicator-based vulnerability assessment methodologies. After a general discussion, the more practical aspects of methodological development were addressed. The various advantages, disadvantages and implications of using this class of methodologies were discussed. A case study

assessment of coastal vulnerability to rapid-onset flooding carried out through an indicator-based methodology was developed in the context of **Paper II**. In the study, a series of inputs pertaining to relevant bio-geophysical variables – including climate data on wind and waves – was utilised to compute a coastal vulnerability index along the shoreline of the study area in the Mediterranean described in Chapter 1.4. There is a high degree of uncertainty about the future evolution of ESLs in the Mediterranean Sea basin, but climate variability is nevertheless crucial in determining vulnerability to coastal flooding. There is a paucity of literature focusing on the extent to which indicator-based vulnerability assessment methods can be used to account for and reflect variations in the climatic conditions underlying the generation of extreme sea levels. In order to explore this area of research, the study focused on the sensitivity of the method to variations in climate data inputs. Study results concluded that some of the aggregation procedures used in the methodology completely masked the variations found in the raw climate data. This in turn is a serious limitation in terms of considering vulnerability as a measure of possible future harm.

The fourth chapter of the thesis dealt with the topic of flood susceptibility in coastal areas. The decision to adopt this perspective in the final phase of the research was driven by the need to narrow down the number of coastal system elements to be considered in order to achieve the objective of having a greater level of detail on the natural conditions that contribute to flood vulnerability and to be able to achieve a desired type of spatial representation different from that obtained before. Within this context, a data-driven flood susceptibility assessment aimed at the identification of areas potentially subject to flooding was developed in **Paper III** for the same study area as before. All the main potential flood drivers were taken into account, including coastal, pluvial and fluvial. The article shows that this method can be used to identify flood-prone areas fairly reliably and without excessive computational resources, even if some further research is required to improve results, as outlined in more detail in Section 5.2 below.

As noted by Bove et al. [99], a gap exists between large-scale, non-specific flood assessments and single-facility detailed assessments, where the latter are too costly to develop in a systematic manner across wide regions and the former are too generic to target elements that might be of interest to set up climate adaptation plans and disaster risk reduction strategies. The research carried out for **Paper II** showed that the approach adopted therein falls into the first category. Although generally applicable, the limitations of the methodology result in a very narrow scope of application as a

decision support tool for climate resilience.
On the other hand, the methodology adopted in the context of **Paper III** can represent a *middle-ground* approach able to reconcile the need for accuracy in the identification of flood-prone areas with the possible time and resource constraints that might characterise several of the phases involved in disaster management.

5.1 Generalisability of Results

The question of the generalisability of the results of the research presented in this thesis is discussed in this section, specifically in relation to the two case studies developed in **Paper II** and **Paper III**. In both cases, it may be useful to highlight whether the results of the analysis are applicable to coastal areas characterised by similar geomorphological or climatic conditions. A discussion of the generalisability of the case study results and the generalisability of the methodological implications highlighted by the case study application is presented here.

The results of **Paper II** highlighted comparatively higher levels of vulnerability in coastal stretches characterised by extensive and complex coastal infrastructure, such as breakwaters and other portal features, and a spatial clustering of areas considered more vulnerable due to their geomorphological conformation (namely low relief). This was observed in correspondence of the main coastal towns (and their port infrastructure) within the Liguria region. It can be assumed that the application of the InVEST Coastal Vulnerability model to similar areas would reveal similar patterns. On the other hand, the vulnerability driven by the climate data inputs (wind speed and wave power) showed less spatial clustering behaviour. However, the cause of this pattern – or lack thereof – is likely to be due to the spatial interpolation strategy used within the model to link the position of the ERA5 points (located at sea) to the coastline.
At the time of publication, **Paper II** was the only example of a scientific article using the InVEST Coastal Vulnerability model within the Mediterranean basin. The paper by Papasarafianou et al. [100] is the only publication using the model for a Mediterranean study area published between the time of writing **Paper II** and the time of writing this dissertation. In Papasarafianou et al. [100] the InVEST model is used to assess storm induced coastal erosion as part of a holistic approach that

also uses other models for sediment production and transport and sediment retention in flood affected areas of a Greek island. The authors found similar patterns in the model results, with model outputs showing levels of vulnerability that varied in relation to coastal elevation. In addition, similar marine and coastal habitats to those found in **Paper II** were found in the Greek island, with relatively low protective potential, such as seagrass.
Other considerations of generalisability to other areas, beyond the very general ones just mentioned, are not applicable in this case. As discussed in **Paper II**, the qualitative and relative nature of the assessment methodology used, as well as the aggregation of the index, does not allow for *a priori* comparisons between assessments carried out in different areas. In addition, the large number of variables involved in the generation of the overall vulnerability index makes it difficult to compare the causes of particular levels of vulnerability for individual stretches of coastline. A more scientifically sound approach to testing the generalisability of the results obtained is proposed in section 5.2 below.
On the other hand, the methodological implications of the research developed in **Paper II** can be assumed to be highly generalisable. Namely, the insensitivity of model results to variations in climate data inputs would hold true for any coastal area in the world to which the InVEST Coastal Vulnerability model might be applied, as it is rooted in the index construction methodology. This would also apply to any IBVA methodology based on comparable assumptions and methodologies underlying index aggregation and calculation.

The assessment of the generalisability of the results in the context of **Paper III** would theoretically require an assessment for coastal areas that are similar to Liguria from a climatic and geomorphological point of view. Nevertheless, it is noteworthy that within the susceptibility assessment developed for this work, the climatic variation at the base of the hazard is embedded in the numerical flood models used to train the machine learning models. Furthermore, most of the information on the frequency of marine flooding events is lost, as only the maximum flood extent is considered, and the medium probability scenario considered also varies from place to place.
As the assessment presented in **Paper III** is a susceptibility assessment, it would be more scientifically accurate to consider the generalisability only in terms of the geomorphological characteristics of the coastal area under consideration. Some aspects

of this have been discussed in detail in the article. Among these, the most noteworthy was related to the better performance of the classification models used in non-flat terrain. It follows that the approach of the study is unlikely to be generalisable to coastal areas characterised by flatter and more complex terrain than the one analysed. Additional limitations to the generalisability of the approach are related to the effect of the spatial resolution on the accuracy of the model. It should be noted that the relatively coarse spatial resolution used in the study and the lack of data on subsurface flow, which may be critical in some areas, would make the approach presented in the study inappropriate for areas that may have undergone extensive infrastructure adaptation to increase water flow during flood events. Some potential future research directions in this area are discussed in section 5.2.

5.2 Future Research Directions

In the first case study developed in the context of this dissertation, an attempt was made to explore the possibilities of incorporating climate data into the different methodologies. The main problem was the integration of data pertaining to processes happening at different spatial and temporal scales, which is a well-known limitation for vulnerability assessments in general as described in Chapters 1 and 3. Future research should focus on shedding some light on some of the shortcomings identified through **Paper II**, namely:

1. Assessing whether there is a way to account for climate variability within IBVA methodologies, or if the results achieved in the context of the research developed hold in general.

2. The processes behind climate change-driven risks and vulnerability are inherently dynamical, yet some of the most widespread methodologies for the assessment of vulnerability seem unable to account for such dynamic nature. Future research should address what link exists between the most simplified flood vulnerability assessment methodologies and the underlying physical processes that result in flooding. Are the assumptions that are made for the sake of simplification based on real-world processes or are they brought to the point of being disconnected from reality?

3. A third possible direction for future research concerns the need to better assess the generalisability of the results obtained in **Paper II**, also in consideration of the limitations in the possibility of comparison between different coastal areas discussed in section 5.1 above. To this end, future research could attempt a case study in which the InVEST Coastal Vulnerability model is applied to a wider coastal stretch, extending from Liguria to areas characterised by similar geomorphological and climatic conditions. The Marseille coast in France could provide such an example.

Another issue that needs to be addressed is the general mismatch between the need to obtain increasingly accurate results, to have increasingly accurate models, and the availability of data to support these needs. This was a limiting factor related to the second case study developed (**Paper III**), where limitations in the data used as ground truth constrained the choice of which training data to use, and the results obtained partly reflected the need to use more accurate data in morphologically complex coastal contexts. It comes from this that:

1. On a general note, future research should focus on increasing the overall availability and quality of both post-event and modelled data on coastal flooding.

2. From a more specific perspective, future research should focus on improving the results achieved in the context of **Paper III**, namely in terms of evaluating whether utilising a more detailed ground truth data in conjunction with more complex deep learning models might lead to achieving better classification results.

3. The results of the analysis carried out in **Paper III** could also be useful in guiding the collection of more accurate datasets in coastal areas, as the lack of accurate data for both predictors and ground truth was identified as one of the main limitations of the study. Specifically, the approach could be used in coastal areas with a similar conformation to that proposed in the study as a means of highlighting regions that might require more specific assessment. Examples of this could be areas where the model may indicate a particularly large area as susceptible to flooding, where more detailed analysis may be required to better identify the different levels of risk within the area and to design preparedness plans. This is particularly important for areas where the conformation of the built environment or the presence of underground drainage

systems is not correctly captured, if at all, in the digital elevation model and other ground-based predictors used in the analysis.

References

[1] Ap van Dongeren, Paolo Ciavola, Grit Martinez, Christophe Viavattene, Tom Bogaard, Oscar Ferreira, Ruth Higgins, and Robert McCall. Introduction to risc-kit: Resilience-increasing strategies for coasts. *Coastal Engineering*, 134:2–9, 2018. RISC-KIT: Resilience-increasing Strategies for Coasts – Toolkit.

[2] Gonzalo Mateo-Garcia, Joshua Veitch-Michaelis, Lewis Smith, Silviu Vlad Oprea, Guy Schumann, Yarin Gal, Atılım Güneş Baydin, and Dietmar Backes. Towards global flood mapping onboard low cost satellites with machine learning. *Scientific Reports*, 11(1):7249, March 2021.

[3] Enrique Portalés-Julià, Gonzalo Mateo-García, Cormac Purcell, and Luis Gómez-Chova. Global flood extent segmentation in optical satellite images. *Scientific Reports*, 13(1):20316, November 2023.

[4] E. Ali, W. Cramer, J. Carnicer, E. Georgopoulou, N.J.M. Hilmi, G. Le Cozannet, and P. Lionello. Cross-chapter paper 4: Mediterranean region. in: Climate change 2022: Impacts, adaptation and vulnerability. contribution of working group ii to the sixth assessment report of the intergovernmental panel on climate change. cambridge university press, cambridge, uk and new york, ny, usa., 2022.

[5] James J. McCarthy, Osvaldo F. Canziani, Neil A. Leary, David J. Dokken, and Kasey S. White. *Climate Change 2001: Impacts, Adaptation, and Vulnerability: Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press, Cambridge., 2001. (Eds.).

[6] Jochen Hinkel. "indicators of vulnerability and adaptive capacity": Towards a clarification of the science–policy interface. *Global Environmental Change*, 21(1):198–208, 2011.

[7] Gilberto Gallopín. Human dimensions of global change: linking the global and the local processes. *International Social Science Journal*, 43:707–718, 01 1991.

[8] B L II Turner, Roger Kasperson, Pamela Matson, James Mccarthy, Robert Corell, Lindsey Christensen, Noelle Selin, Jeanne Kasperson, Amy Luers,

Marybeth Martello, Colin Polsky, Alexander Pulsipher, and Andrew Schiller. A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences of the United States of America*, 100:8074–9, 08 2003.

[9] S. H. Eriksen and P. M. Kelly. Developing credible vulnerability indicators for climate adaptation policy assessment. *Mitigation and Adaptation Strategies for Global Change*, 12(4):495–524, 2007.

[10] Fahim N. Tonmoy, Abbas El-Zein, and Jochen Hinkel. Assessment of vulnerability to climate change using indicators: a meta-analysis of the literature. *WIREs Climate Change*, 5(6):775–792, 2014.

[11] Marco A. Janssen and Elinor Ostrom. Resilience, vulnerability, and adaptation: A cross-cutting theme of the international human dimensions programme on global environmental change. *Global Environmental Change*, 16(3):237–239, 2006. Resilience, Vulnerability, and Adaptation: A Cross-Cutting Theme of the International Human Dimensions Programme on Global Environmental Change.

[12] W. Cramer and K. Guiot, J.and Marini. Medecc (2020) climate and environmental change in the mediterranean basin – current situation and risks for the future. first mediterranean assessment report. Union for the Mediterranean, Plan Bleu, UNEP/MAP, Marseille, France, 2020.

[13] Wolfgang Cramer, Joël Guiot, Marianela Fader, Joaquim Garrabou, Jean-Pierre Gattuso, Ana Iglesias, Manfred A. Lange, Piero Lionello, Maria Carmen Llasat, Shlomit Paz, Josep Peñuelas, Maria Snoussi, Andrea Toreti, Michael N. Tsimplis, and Elena Xoplaki. Climate change and interconnected risks to sustainable development in the mediterranean. *Nature Climate Change*, 8(11):972–980, 2018.

[14] Stéphanie Thiébault, Jean-Paul Moatti, Eds, V. Ducrocq, Eric Gaume, François Dulac, E. Hamonou, Yunne-Jai Shin, Guiot Joel, Gilles Boulet, Jean-François Guégan, Robert Barouki, Isabella Annesi-Mae, Pascal Marty, Emmanuel Torquebiau, Jean-François Sou, Yildiz Aumeeruddy-Thomas, Jean-Luc Chotte, and Denis Lacroix. *The Mediterranean Region Under Climate Change. A Scientific Update*. 01 2016.

[15] F. M. Calafat, E. Avgoustoglou, G. Jordà, H. Flocas, G. Zodiatis, M. N. Tsimplis, and J. Kouroutzoglou. The ability of a barotropic model to simulate sea level extremes of meteorological origin in the mediterranean sea, including those caused by explosive cyclones. *Journal of Geophysical Research: Oceans*, 119(11):7840–7853, 2014.

[16] Yannis S. Androulidakis, Katerina D. Kombiadou, Christos V. Makris, Vassilis N. Baltikas, and Yannis N. Krestenitis. Storm surges in the mediterranean sea: Variability and trends under future climatic conditions. *Dynamics of Atmospheres and Oceans*, 71:56–82, 2015.

[17] Michalis I. Vousdoukas, Lorenzo Mentaschi, Evangelos Voukouvalas, Martin Verlaan, and Luc Feyen. Extreme sea levels on the rise along europe's coasts. *Earth's Future*, 5(3):304–323, 2017.

[18] P. Lionello, D. Barriopedro, C. Ferrarin, R. J. Nicholls, M. Orlić, F. Raicich, M. Reale, G. Umgiesser, M. Vousdoukas, and D. Zanchettin. Extreme floods of venice: characteristics, dynamics, past and future evolution (review article). *Natural Hazards and Earth System Sciences*, 21(8):2705–2731, 2021.

[19] Marta Marcos, Gabriel Jordà, Damià Gomis, and Begoña Pérez. Changes in storm surges in southern europe from a regional model under climate change scenarios. *Global and Planetary Change*, 77(3):116–128, 2011.

[20] D. Conte and P. Lionello. Characteristics of large positive and negative surges in the mediterranean sea and their attenuation in future climate scenarios. *Global and Planetary Change*, 111:159–173, 2013.

[21] P. Lionello, S. Cogo, M.B. Galati, and A. Sanna. The mediterranean surface wave climate inferred from future scenario simulations. *Global and Planetary Change*, 63(2):152–162, 2008. Mediterranean climate: trends, variability and change.

[22] Michalis I. Vousdoukas, Lorenzo Mentaschi, Evangelos Voukouvalas, Alessandra Bianchi, Francesco Dottori, and Luc Feyen. Climatic and socioeconomic controls of future coastal flood risk in europe. *Nature Climate Change*, 8(9):776–780, 2018.

[23] Robert J. Nicholls, Frank M.J. Hoozemans, and Marcel Marchand. Increasing flood risk and wetland losses due to global sea-level rise: regional and global analyses. *Global Environmental Change*, 9:S69–S87, 1999.

[24] José A. Jiménez, Herminia I. Valdemoro, Eva Bosom, Agustín Sánchez-Arcilla, and Robert J. Nicholls. Impacts of sea-level rise-induced erosion on the catalan coast. *Regional Environmental Change*, 17(2):593–603, 2017.

[25] O.D. Cardona, M.K. van Aalst, M Birkmann, G Fordham, G. McGregor, R. Perez, R.S. Pulwarty, E.L.F. Schipper, and B.T Sinh. Determinants of risk: exposure and vulnerability. in: Managing the risks of extreme events and disasters to advance climate change adaptation. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 65-108, 2012.

[26] R. Bentivoglio, E. Isufi, S. N. Jonkman, and R. Taormina. Deep learning methods for flood mapping: a review of existing applications and future research directions. *Hydrology and Earth System Sciences*, 26(16):4345–4378, 2022.

[27] Agenzia Regionale per la Protezione dell'Ambiente Ligure (ARPAL). Atlante climatico della liguria. https://www.arpal.liguria.it/contenuti$_statici/clima/atlante/Atlante_climatico_della_Liguria.pdf,20$

[28] Ministero dell'Ambiente e della tuela del territorio e del mare. Piano nazionale di adattamento ai cambiamenti climatici. https://www.mase.gov.it/sites/default/files/archivio/allegati/clima/pnacc.pdf, 2018.

[29] Carlotta Quagliolo, Elena Comino, and Alessandro Pezzoli. Experimental flash floods assessment through urban flood risk mitigation (ufrm) model: The case study of ligurian coastal cities. *Frontiers in Water*, 3, 2021.

[30] P. Brandolini, A. Cevasco, M. Firpo, A. Robbiano, and A. Sacchini. Geo-hydrological risk management for civil protection purposes in the urban area of genoa (liguria, nw italy). *Natural Hazards and Earth System Sciences*, 12(4):943–959, 2012.

[31] Pierluigi Brandolini and R. Terranova. Effects of the september, 1992 flood in the areas of genoa and savona (liguria, northern italy). *Il Quaternario*, 7:473–478, 01 1994.

[32] Martina Raffellini, Federica Martina, Francesco Silvestro, Francesca Giannoni, and Nicola Rebora. Performance evaluation of a nowcasting modelling chain operatively employed in very small catchments in the mediterranean environment for civil protection purposes. *Atmosphere*, 12(6), 2021.

[33] F. Silvestro, N. Rebora, L. Rossi, D. Dolia, S. Gabellani, F. Pignone, E. Trasforini, R. Rudari, S. De Angeli, and C. Masciulli. What if the 25 october 2011 event that struck cinque terre (liguria) had happened in genoa, italy? flooding scenarios, hazard mapping and damage estimation. *Natural Hazards and Earth System Sciences*, 16(8):1737–1753, 2016.

[34] F. Silvestro, L. Rossi, L. Campo, A. Parodi, E. Fiori, R. Rudari, and L. Ferraris. Impact-based flash-flood forecasting system: Sensitivity to high resolution numerical weather prediction systems and soil moisture. *Journal of Hydrology*, 572:388–402, 2019.

[35] M. L. Poletti, F. Silvestro, S. Davolio, F. Pignone, and N. Rebora. Using nowcasting technique and data assimilation in a meteorological model to improve very short range hydrological forecasts. *Hydrology and Earth System Sciences*, 23(9):3823–3841, 2019.

[36] A. Palla, M. Colli, A. Candela, G.T. Aronica, and L.G. Lanza. Pluvial flooding in urban areas: the role of surface drainage efficiency. *Journal of Flood Risk Management*, 11(S2):S663–S676, 2018.

[37] E. Garnier, P. Ciavola, T. Spencer, O. Ferreira, C. Armaroli, and A. McIvor. Historical analysis of storm events: Case studies in france, england, portugal and italy. *Coastal Engineering*, 134:10–23, 2018. RISC-KIT: Resilience-increasing Strategies for Coasts – Toolkit.

[38] A. Oprandi, L. Mucerino, F. De Leo, C.N. Bianchi, C. Morri, A. Azzola, F. Benelli, G. Besio, M. Ferrari, and M. Montefalcone. Effects of a severe storm on seagrass meadows. *Science of The Total Environment*, 748:141373, 2020.

[39] Ilaria Ferrando, Pierluigi Brandolini, Bianca Federici, Antonio Lucarelli, Domenico Sguerso, Danilo Morelli, and Nicola Corradi. Coastal modification in relation to sea storm effects: Application of 3d remote sensing survey in sanremo marina (liguria, nw italy). *Water*, 13(8), 2021.

[40] Alice Re, Lorenzo Minola, and Alessandro Pezzoli. Climate scenarios for coastal flood vulnerability assessments: A case study for the ligurian coastal region. *Climate*, 11(3), 2023.

[41] A. Re, L. Minola, A. Pezzoli, and G. Camps-Valls. Predicting coastal flooding in the mediterranean with remote sensing and machine learning. EGU General Assembly 2024, Vienna, Austria, 14–19 Apr 2024, EGU24-9306, 2024.

[42] A. Pesci, G. Teza, M. Bisson, F. Muccini, P. Stefanelli, M. Anzidei, R. Carluccio, I. Nicolosi, A. Galvani, V. Sepe, and C. Carmisciano. Monitoring of a coastal zone by independent fast photogrammetric surveys: the case of monterosso a mare (ligurian sea, italy). *Journal of Geosciences and Geomatics*, 4(4):73–81, 2016.

[43] Carola Colangeli, Agnese Baldoni, Lorenzo Melito, Sara Corvaro, and Maurizio Brocchini. Harbour hydro-morphodynamics and freshwater discharges: The la spezia arsenale case. *Water*, 15(16), 2023.

[44] B. Federici, N. Corradi, I. Ferrando, D. Sguerso, A. Lucarelli, S. Guida, and P. Brandolini. Remote sensing techniques applied to geomorphological mapping of rocky coast: the case study of gallinara island (western liguria, italy). *European Journal of Remote Sensing*, 52(sup4):123–136, 2019.

[45] A. Guarnieri, S. Saremi, A. Pedroncini, J. H. Jensen, S. Torretta, M. Vaccari, and C. Vincenzi. Effects of marine traffic on sediment erosion and accumulation in ports: a new model-based methodology. *Ocean Science*, 17(2):411–430, 2021.

[46] Valentina Vannucchi, Stefano Taddei, Valerio Capecchi, Michele Bendoni, and Carlo Brandini. Dynamical downscaling of era5 data on the north-western mediterranean sea: From atmosphere to high-resolution coastal wave climate. *Journal of Marine Science and Engineering*, 9(2), 2021.

[47] Andrea Lira-Loarca, Alejandro Cáceres-Euse, Francesco De-Leo, and Giovanni Besio. Wave modeling with unstructured mesh for hindcast, forecast and wave hazard applications in the mediterranean sea. *Applied Ocean Research*, 122:103118, 2022.

[48] Silvia De Angeli, Mirko D'Andrea, Giacomo Cazzola, Daniele Dolia, Enrico Duo, and Nicola Rebora. Coastal risk assessment framework: Comparison of modelled fluvial and marine inundation impacts, bocca di magra, ligurian coast, italy. *Coastal Engineering*, 134:229–240, 2018. RISC-KIT: Resilience-increasing Strategies for Coasts – Toolkit.

[49] Maria Francesca Bruno, Giulia Motta Zanin, Angela Barbanente, and Leonardo Damiani. Understanding the cognitive components of coastal risk assessment. *Journal of Marine Science and Engineering*, 9(7), 2021.

[50] Jochen Hinkel and Richard J.T. Klein. Integrating knowledge to assess coastal vulnerability to sea-level rise: The development of the diva tool. *Global Environmental Change*, 19(3):384–395, 2009.

[51] S. Torresan, A. Critto, J. Rizzi, and A. Marcomini. Assessment of coastal vulnerability to climate change hazards at the regional scale: the case study of the north adriatic sea. *Natural Hazards and Earth System Sciences*, 12(7):2347–2368, 2012.

[52] Barbara Zanuttigh. Coastal flood protection: What perspective in a changing climate? the theseus approach. *Environmental Science Policy*, 14(7):845–863, 2011. Adapting to Climate Change: Reducing Water-related Risks in Europe.

[53] Barbara Zanuttigh, Dario Simcic, Stefano Bagli, Fabio Bozzeda, Luca Pietrantoni, Fabio Zagonari, Simon Hoggart, and Robert J. Nicholls. Theseus decision support system for coastal risk management. *Coastal Engineering*, 87:218–239, 2014. Coasts@Risks: THESEUS, a new wave in coastal protection.

[54] UNISDR. Sendai framework for disaster risk reduction 2015 - 2030. https://www.unisdr.org/files/43291$_sendaiframeworkfordrren.pdf$, 2015.

[55] Chua Thia-Eng. Essential elements of integrated coastal zone management. *Ocean Coastal Management*, 21(1):81–108, 1993. Integrated Coastal Management.

[56] Brian Shipman and Tim Stojanovic. Facts, fictions, and failures of integrated coastal zone management in europe. *Coastal Management*, 35(2-3):375–398, 2007.

[57] European Environment Agency. Eea glossary - iczm, 2000.

[58] Martin W Holdgate. *A perspective of environmental pollution*. Cambridge University Press, 1979.

[59] Xin Fang, Yifei Zhang, Yunyun Xiang, Jiaqi Zou, Xiaoyan Li, Chunling Hao, and Jingchen Wang. A spatial model for coastal flood susceptibility assessment using the 2d-spr method with complex network theory: A case study of a reclamation island in zhoushan, china. *Environmental Impact Assessment Review*, 98:106953, 2023.

[60] E. Evans, J. Hall, E. Penning-Rowsell, P. Sayers, C. Thorne, and A. Watkinson. Future flood risk management in the uk. *Proceedings of the Institution of Civil Engineers - Water Management*, 159(1):53–61, 2006.

[61] Lydia Cumiskey, Sally Priest, Nikolay Valchev, Christophe Viavattene, Susana Costas, and Joseph Clarke. A framework to include the (inter)dependencies of disaster risk reduction measures in coastal risk assessment. *Coastal Engineering*, 134:81–92, 2018. RISC-KIT: Resilience-increasing Strategies for Coasts – Toolkit.

[62] Marie Coquet, Denis Mercier, and Ghozlane Fleury-Bahi. Individuals' perceptions of areas exposed to coastal flooding in four french coastal municipalities: the contribution of sketch mapping. *Geoenvironmental Disasters*, 5(1), 2018.

[63] Sylvain Elineau, Esméralda Longépée, Lydie Goeldner-Gianella, Alexandre Alexandre Nicolae-Lerma, Paul Durand, and Brice Anselme. Understanding coastal flood risk prevention by combining modelling and sketch maps (mediterranean coast, france). *Environmental Hazards*, 20(5):457–476, 2021.

[64] Mario Andres Fernandez, Santiago Bucaram, and Willington Renteria. (non-) robustness of vulnerability assessments to climate change: An application to new zealand. *Journal of Environmental Management*, 203:400–412, 2017.

[65] Vivien Gornitz. Global coastal hazards from future sea level rise. *Palaeogeography, Palaeoclimatology, Palaeoecology*, 89(4):379–398, 1991.

[66] Vivien M. Gornitz, Richard C. Daniels, Tammy W. White, and Kevin R. Birdwell. The development of a coastal risk assessment database: Vulnerability to sea-level rise in the u.s. southeast. *Journal of Coastal Research*, pages 327–338, 1994.

[67] Natural capital project, 2025. invest 0.0. stanford university, university of minnesota, chinese academy of sciences, the nature conservancy, world wildlife fund, stockholm resilience centre and the royal swedish academy of sciences. https://naturalcapitalproject.stanford.edu/software/invest, 2025.

[68] Jing Ran, Brian H MacGillivray, Yi Gong, and Tristram C Hales. The application of frameworks for measuring social vulnerability and resilience to geophysical hazards within developing countries: A systematic review and narrative synthesis. *Science of The Total Environment*, 711:134486, 2020.

[69] Carolina Schmanech Mussi, Jarbas Bonetti, and Rafael Medeiros Sperb. Coastal sensitivity and population exposure to sea level rise: a case study on santa catarina island, brazil. *Journal of Coastal Conservation*, 22(6):1117–1128, 2018.

[70] Alireza Arabameri, Khalil Rezaei, Artemi Cerdà, Christian Conoscenti, and Zahra Kalantari. A comparison of statistical methods and multi-criteria decision making to map flood hazard susceptibility in northern iran. *Science of The Total Environment*, 660:443–458, 2019.

[71] Andrés F. López-Lopera, Déborah Idier, Jérémy Rohmer, and François Bachoc. Multioutput gaussian processes with functional data: A study on coastal flood hazard assessment. *Reliability Engineering & System Safety*, 218:108139, 2022.

[72] David F. Muñoz, Paul Muñoz, Hamed Moftakhari, and Hamid Moradkhani. From local to regional compound flood mapping with deep learning and data fusion techniques. *Science of The Total Environment*, 782:146927, 2021.

[73] Md. Hasibul Hasan, Asib Ahmed, K.M. Nafee, and Md. Amzed Hossen. Use of machine learning algorithms to assess flood susceptibility in the coastal area of bangladesh. *Ocean & Coastal Management*, 236:106503, 2023.

[74] Zanetti Marco, Allegri Elena, Sperotto Anna, Torresan Silvia, and Critto Andrea. Spatio-temporal cross-validation to predict pluvial flood events in the metropolitan city of venice. *Journal of Hydrology*, 612:128150, 2022.

[75] Esmaeel Dodangeh, Bahram Choubin, Ahmad Najafi Eigdir, Narjes Nabipour, Mehdi Panahi, Shahaboddin Shamshirband, and Amir Mosavi. Integrated machine learning methods with resampling algorithms for flood susceptibility prediction. *Science of The Total Environment*, 705:135983, 2020.

[76] Sang-Jin Park and Dong-Kun Lee. Prediction of coastal flooding risk under climate change impacts in south korea using machine learning algorithms. *Environmental Research Letters*, 15(9):094052, aug 2020.

[77] Mahyat Shafapour Tehrany, Biswajeet Pradhan, and Mustafa Neamah Jebur. Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in gis. *Journal of Hydrology*, 512:332–343, 2014.

[78] Mehebub Sahana, Sufia Rehman, Haroon Sajjad, and Haoyuan Hong. Exploring effectiveness of frequency ratio and support vector machine models in storm surge flood susceptibility assessment: A study of sundarban biosphere reserve, india. *CATENA*, 189:104450, 2020.

[79] Van Tich Vu, Huu Duy Nguyen, Phuong Lan Vu, Minh Cuong Ha, Van Dong Bui, Thi Oanh Nguyen, Van Hiep Hoang, and Thanh Kim Hue Nguyen. Predicting land use effects on flood susceptibility using machine learning and remote sensing in coastal Vietnam. *Water Practice and Technology*, 18(6):1543–1555, 06 2023.

[80] M. I. Vousdoukas, E. Voukouvalas, L. Mentaschi, F. Dottori, A. Giardino, D. Bouziotas, A. Bianchi, P. Salamon, and L. Feyen. Developments in large-scale coastal flood hazard mapping. *Natural Hazards and Earth System Sciences*, 16(8):1841–1853, 2016.

[81] T.W. Gallien, J.E. Schubert, and B.F. Sanders. Predicting tidal flooding of urbanized embayments: A modeling framework and data requirements. *Coastal Engineering*, 58(6):567–577, 2011.

[82] Autorità di Bacino Distrettuale dell'Appennino Settentrionale. Piani di bacino stralcio per l'assetto idrogeologico. http://www.pianidibacino.ambienteinliguria.it/. Accessed: 29/02/2024.

[83] Ebrahim Hamidi, Brad G. Peter, David F. Muñoz, Hamed Moftakhari, and Hamid Moradkhani. Fast flood extent monitoring with sar change detection using google earth engine. *IEEE Transactions on Geoscience and Remote Sensing*, 61:1–19, 2023.

[84] Hanqiu Xu. Modification of normalised difference water index (ndwi) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*, 27(14):3025–3033, 2006.

[85] Kel N. Markert, Farrukh Chishtie, Eric R. Anderson, David Saah, and Robert E. Griffin. On the merging of optical and sar satellite imagery for surface water mapping applications. *Results in Physics*, 9:275–277, 2018.

[86] Y. S. Rao V. S. K. Vanama and C. M. Bhatt. Change detection based flood mapping using multi-temporal earth observation satellite images: 2018 flood event of kerala, india. *European Journal of Remote Sensing*, 54(1):42–58, 2021.

[87] Stephanie Long, Temilola E Fatoyinbo, and Frederick Policelli. Flood extent mapping for namibia using change detection and thresholding with sar. *Environmental Research Letters*, 9(3):035002, mar 2014.

[88] Ebrahim Hamidi, Brad Peter, David F. Muñoz, Hamed Moftakhari, and Hamid Moradkhani. Replication Data for: Fast flood extent monitoring with SAR change detection using Google Earth Engine, 2022.

[89] Fabio Cian, Mattia Marconcini, and Pietro Ceccato. Normalized difference flood index for rapid flood mapping: Taking advantage of eo big data. *Remote Sensing of Environment*, 209:712–730, 2018.

[90] Jean-François Pekel, Andrew Cottam, Noel Gorelick, and Alan S. Belward. High-resolution mapping of global surface water and its long-term changes. *Nature*, 540:418–422, 2016.

[91] Sean A. Woznicki, Jeremy Baynes, Stephanie Panlasigui, Megan Mehaffey, and Anne Neale. Development of a spatially complete floodplain map of the conterminous united states using random forest. *Science of The Total Environment*, 647:942–953, 2019.

[92] R. Hu, F. Fang, C.C. Pain, and I.M. Navon. Rapid spatio-temporal flood prediction and uncertainty quantification using a deep learning method. *Journal of Hydrology*, 575:911–920, 2019.

[93] Jialei Chen, Guoru Huang, and Wenjie Chen. Towards better flood risk management: Assessing flood risk and investigating the potential mechanism based on machine learning models. *Journal of Environmental Management*, 293:112810, 2021.

[94] Lei Fang, Jinliang Huang, Juntao Cai, and Vilas Nitivattananon. Hybrid approach for flood susceptibility assessment in a flood-prone mountainous catchment in china. *Journal of Hydrology*, 612:128091, 2022.

[95] Roland Löwe, Julian Böhm, David Getreuer Jensen, Jorge Leandro, and Søren Højmark Rasmussen. U-flood – topographic deep learning for predicting urban pluvial flood water depth. *Journal of Hydrology*, 603:126898, 2021.

[96] Zifeng Guo, Vahid Moosavi, and João P. Leitão. Data-driven rapid flood prediction mapping with catchment generalizability. *Journal of Hydrology*, 609:127726, 2022.

[97] E. F. Asbridge, D. Low Choy, B. Mackey, S. Serrao-Neumann, P. Taygfeld, and K. Rogers. Coastal flood risk within a peri-urban area: Sussex inlet district, se australia. *Natural Hazards*, 109(1):999–1026, 2019.

[98] Kerrylee Rogers and Colin D. Woodroffe. Geomorphology as an indicator of the biophysical vulnerability of estuaries to coastal and flood hazards in a changing climate. *Journal of Coastal Conservation*, 20(2):127–144, 2016.

[99] Gerald Bove, Austin Becker, Benjamin Sweeney, Michalis Vousdoukas, and Scott Kulp. A method for regional estimation of climate change exposure of coastal infrastructure: Case of usvi and the influence of digital elevation models on assessments. *Science of The Total Environment*, 710:136162, 2020.

[100] Stamatia Papasarafianou, Ilias Siarkos, Aliki Gkaifyllia, Stavros Sahtouris, Giada Varra, Antonis Chatzipavlis, Thomas Hasiotis, and Ourania Tzoraki. A holistic approach for coastal–watershed management on tourist islands: A case study from petra–molyvos coast, lesvos island (greece). *Geosciences*, 14(12), 2024.

Appendix A

Appended Papers

water

MDPI

Review

Modelling and Mapping Rapid-Onset Coastal Flooding: A Systematic Literature Review

Alice Re [1,*], Lorenzo Minola [1,2,3] and Alessandro Pezzoli [1]

[1] Interuniversity Department of Regional and Urban Studies and Planning (DIST), Politecnico and University of Turin, 10125 Turin, Italy; lorenzo.minola@gmail.com (L.M.); alessandro.pezzoli@polito.it (A.P.)
[2] Regional Climate Group, Department of Earth Sciences, University of Gothenburg, 405 30 Gothenburg, Sweden
[3] Centro de Investigaciones Sobre Desertificación, Consejo Superior de Investigaciones Científicas (CIDE, CSIC-UV-Generalitat Valenciana), Climate, Atmosphere and Ocean Laboratory (Climatoc-Lab), 46113 Moncada, Valencia, Spain
* Correspondence: alice.re@polito.it

Abstract: Increases in the magnitude and frequency of extreme flood events are among the most impactful consequences of climate change. Coastal areas can potentially be affected by interactions among different flood drivers at the interface of terrestrial and marine ecosystems. At the same time, socio-economic processes of population growth and urbanization can lead to increases in local vulnerability to climate extremes in coastal areas. Within this context, research focusing on modelling and mapping rapid-onset coastal flooding is essential (a) to support flood risk management, (b) to design local climate adaptation policies and (c) to increase climate resilience of coastal communities. This systematic literature review delineates the state-of-the art of research on rapid-onset coastal flooding. It provides a comprehensive picture of the broad range of methodologies utilised to model flooding and highlights the commonly identified issues, both from a scientific standpoint and in terms of the policy implications of translating research outputs into actionable information. As flood maps represent fundamental instruments in the communication of research outcomes to support decision making and increase climate resilience, a focus on the spatial representation of coastal floods proposed in the literature is adopted in this review.

Keywords: coastal flooding; sea level rise; climate change; flood modeling; flood mapping

check for updates

Academic Editors: Nawin Raj, Lila Singh-Peterson and Nathan Downs

Received: 12 January 2025
Revised: 11 February 2025
Accepted: 14 February 2025
Published: 19 February 2025

Citation: Re, A.; Minola, L.; Pezzoli, A. Modelling and Mapping Rapid-Onset Coastal Flooding: A Systematic Literature Review. *Water* **2025**, *17*, 599. https://doi.org/10.3390/w17040599

1. Introduction

Coastal areas are particularly susceptible to climate change-related extreme events because of their location at the intersection between marine and land systems, which makes them susceptible to being affected by a combination of fluvial, pluvial and coastal flood drivers [1]. In light of these factors, increasing information is needed to support flood disaster prevention and coastal risk management, and considerable research addressing coastal flooding has been developed in recent times in numerous disciplinary fields [2,3].

Maps are one of the most commonly produced outputs of coastal flood modelling, as they represent important instruments for understanding and communicating complex flooding processes. The role of maps for conveying information and supporting decision making is crucial especially for the communication of climate-related risks in densely populated urban environments, where the multifaceted components of risk and their interactions must be jointly represented [4].

Preventive modelling and mapping applications are especially relevant in the context of disaster prevention, as often climate-related hazards have never been observed before for a given area. To that extent, the simulation of design flood events and the identification of areas potentially affected by coastal floods for different climate change scenarios are crucial.

Within this context, the objective of this systematic literature review is to delineate in a systematic way the extensive scientific research on modelling and mapping rapid-onset floods in coastal areas, focusing on preventive flood assessments because of their role in supporting coastal planning, adaptation policies and flood risk management strategies. It aims to identify the most relevant research gaps in the field, to assess the strengths and drawbacks of the considered individual methodologies, and to highlight the peculiarities resulting from mapping flooding specifically in coastal areas. This review further aims to highlight how different methodologies are used to describe variable configurations of the individual components of the coastal flood system, including the drivers and sources of flooding in coastal areas, the water–land coastal interface, the disaster-receiving body, the consequences of flooding and their complex interactions. Within this framework, a dedicated focus is placed on the disaster-receiving body, thus analyzing the spatial development of floods on emergent portions of coastal areas.

By examining a broad research spectrum, this work further allows for capturing the state-of-the-art of proposed risk mitigation and coastal adaptation strategies, and contributes by highlighting the role of flood research in supporting policymaking as envisioned by the scientific community.

Some overlap exists between the scope of this work and that of some previously published review articles. However, previous studies adopted either an exclusive focus on coastal flood mapping through a narrow set of methodologies, or focused on a wider array of methodologies to map other types of floods—mostly pluvial or fluvial [5,6]. Within the former class of publications, Ferreira et al. [7] analysed process-based indicators for sandy coasts subject to storm-induced hazards. Thorough reviews on numerical modelling of coastal flooding were proposed by Gallien et al. [8] and Santiago-Collazo et al. [9], who investigated, respectively, the modelling of wave overtopping in defended urban backshores and the integration of numerical models describing different flood drivers for compound coastal flood modelling. Among the second type of works identified, Mudashiru et al. [10,11] reviewed flood hazard and susceptibility mapping with a comprehensive approach in terms of the methodologies considered but without a specific focus on coastal flooding. Avila-Aceves et al. [2] analysed the geospatial modelling of pluvial and fluvial flooding, highlighting the wide array of methodologies utilised to study floods in general (including hydrologic/hydraulic modelling, GIS-based Multi Criteria Decision Analysis (MCDA) and Machine Learning (ML)). Bentivoglio et al. [6] reviewed Deep Learning (DL) methodologies for flood mapping for a variety of flood drivers, considering both preventive and post-event flood mapping. In the introduction of a book contribution, Batista [12] adopted a perspective similar to the one proposed in this work and analysed within a general outlook the methodologies utilised in the literature for coastal flood hazard mapping, providing a base for the analysis which could be further expanded and systematised. A more extensive effort was presented by Vousdoukas et al. [13], who investigated large-scale coastal flood hazard mapping due to extreme marine events through a wide series of approaches—including simplified models, semi-dynamic models, dynamic models and the flood intensity index approach.

To the best of the authors' knowledge, at the time of writing, this work is the first to propose a comprehensive and systematic picture of the state-of-the-art of all available methodologies used for pre-event coastal flood modelling and mapping. Because of the broad scope adopted in terms of methodologies considered, this systematic literature review might be further characterised as a systematic scoping review [14,15].

The remainder of this article is organised as follows. The systematic protocol utilised to develop this review is laid out in Section 2. In Section 3, the review results are presented mirroring the various components of the coastal flood system. Section 4 outlines the methodological state-of-the-art of coastal flood modelling. The different types of coastal flood maps proposed are analysed in Section 5. Section 6 addresses the policy implications of the reviewed literature. Discussion is provided and conclusions are drawn in Section 7.

2. Systematic Review Protocol

This study was carried out following a systematic review protocol based on the Joanna Briggs Institute (JBI) guidelines for scoping reviews [16] in order to define *a priori* the objectives, methods and reporting of the review. The adopted workflow was composed of a data identification phase, a screening phase and a full-text examination phase as detailed in Figure 1. All phases were informed by the criteria for article inclusion summarised in Table 1 and detailed in Sections 2.1 and 2.2.

Table 1. Inclusion and exclusion criteria utilised for selection of articles.

Criterion	DSPRC/PICOC Component	Explanation
Climate criterion	Driver	The article must not focus exclusively on climate variation, time series or extreme value analysis, or the development of climate scenarios or projections.
Multi-hazard criterion	Driver/Source	The article must not focus exclusively on multi-hazard assessment.
Hazard criterion	Source	The article must not focus exclusively on long-term SLR, pluvial-only or fluvial-only floods in coastal areas.
Oceanography criterion	Source	The article must not focus exclusively on water dynamics without providing estimates of inland flood development.
Engineering criterion	Pathway	The article must analyse the performance and/or effectiveness of coastal protection infrastructure without providing maps of the extent of the coastal flood.
NBS criterion	Pathway	The article must not analyse the performance and/or effectiveness of NBS or ecosystems in reducing coastal flood risk without providing maps of the extent of the coastal flood.
Ecosystem criterion	Consequence	The article must not focus exclusively on the consequences of coastal flooding in terms of resulting modifications in ecosystem health and distribution.
Methodological criterion	Intervention	The article abstract must mention at least one of the method-related keywords utilised in the database query.
Post-event criterion	Context	The article must not focus exclusively on post-event flood mapping.
Spatial criteria	Outcome	At least one map proposed in the article must conform to the spatial criteria detailed in Section 2.2.
Groundwater criterion	-	The article must not focus exclusively on groundwater-driven flooding or on groundwater contribution to coastal flooding.
Residual criterion	-	The article should have been discarded in the previous selection phases.

During the data identification phase, research articles were retrieved based on a keyword search string and additional search parameters from two databases (Scopus and Web of Science) as detailed in Table 2 [17–19]. Early access papers, proceeding papers, book chapters and data papers were excluded from the search. This selective approach to publication types ensures that the review captures fully developed, peer-reviewed research that has undergone rigorous quality control processes, as journal publications typically follow more consistent reporting formats and validation requirements than other publication types.

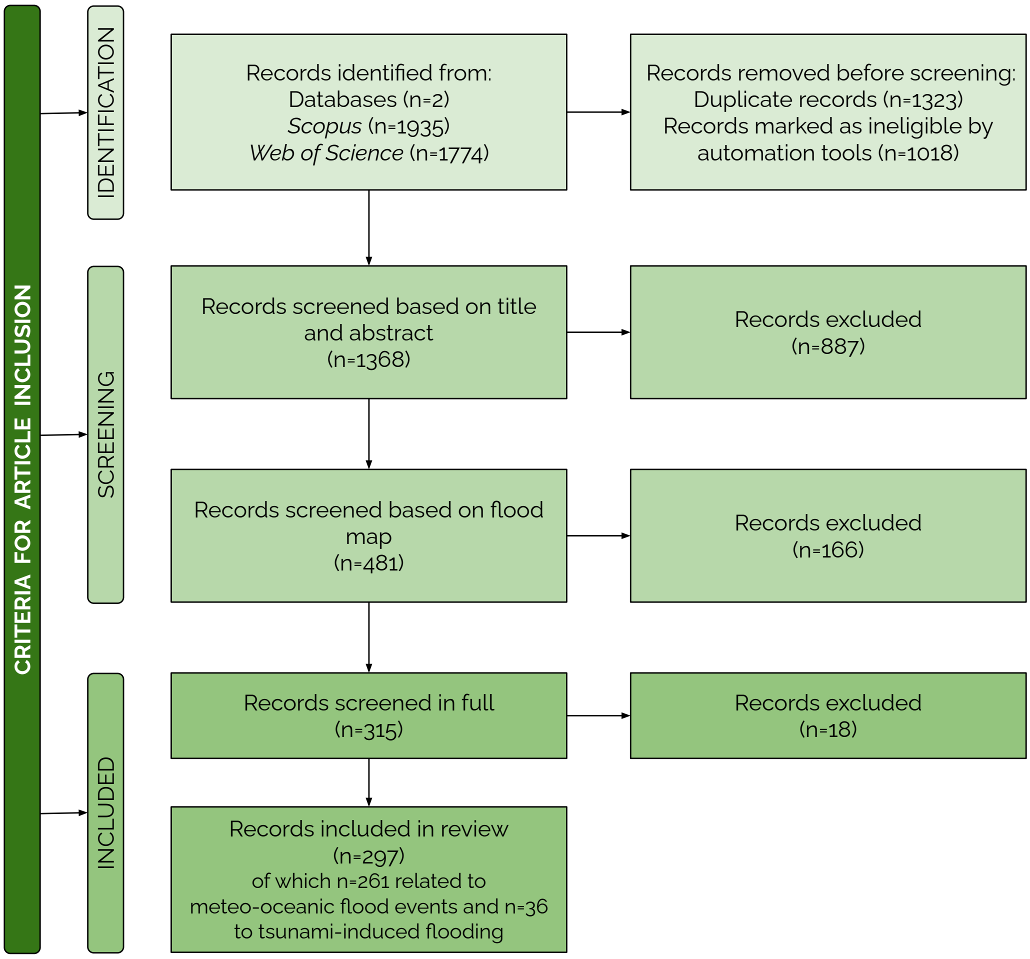

Figure 1. Flow diagram of article identification and screening procedures drafted according to PRISMA2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [20].

Citation data, bibliographical information, full abstract text and keywords were retrieved for identified articles. The two datasets were then filtered individually to remove within-dataset duplicates and articles for which relevant information was missing (i.e., missing DOI). The two datasets were then merged (n = 3709) and duplicates (n = 1323) were removed from the merged dataset. A series of automatic checks on the title and abstract were put in place based on regular expression selection. Specifically, the article abstract had to contain at least one of the keywords pertaining to the eligible research methodologies identified in the keyword search string, to further corroborate the automatic filtering carried out by the database search engine. Furthermore, the abstract was not to contain a series of words that strictly identify unrelated research fields. The final dataset eligible for screening consisted of 1368 articles.

The data screening phase was articulated into a first stage in which articles were manually selected based on the compliance of their abstract and title to the article selection criteria. A quick full-text examination was carried out whenever the title and abstract alone did not provide enough information to determine the fulfilment of one or more criteria. The second stage of the screening process was centred around the flood maps included in the articles. After visual examination, only articles providing a map conforming to the identified criteria for spatial flood representation (see Section 2.2) were selected. A total of 315 articles remained at the end of the screening process. A summary of the motivations for article elimination based on map characteristics is provided in Table 3.

Table 2. Parameters used for retrieval of studies from Scopus and Web of Science databases. Search was carried out on 21 February 2024.

	Scopus	**Web of Science**
Fields Searched	title, abstract, keywords	title, abstract, author keywords
Search String (full)	TITLE-ABS-KEY (coast* AND (flood* OR overflow* OR overtop* OR "inundation") AND ("hazard" OR "susceptibility" OR "risk" OR "exposure" OR "vulnerability") AND (map* OR model*) AND ("numerical" OR "physically-based" OR "hydrologic" OR "hydraulic" OR "hydrodynamic" OR "simplified" OR "GIS" OR "static" OR "empirical" OR "data-driven" OR "multi-criteria" OR mcd* OR "machine learning" OR "deep learning" OR "artificial intelligence" OR "statistical" OR indicator* OR "index")) AND PUBYEAR > 2009 AND PUBYEAR < 2024 AND (LIMIT-TO (SUBJAREA, "ENVI") OR LIMIT-TO (SUBJAREA, "EART") OR LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re"))	coast* AND (flood* OR overflow* OR overtop* OR "inundation") AND ("hazard" OR "susceptibility" OR "risk" OR "exposure" OR "vulnerability") AND (map* OR model*) AND ("numerical" OR "physically-based" OR "hydrologic" OR "hydraulic" OR "hydrodynamic" OR "simplified" OR "GIS" OR "static" OR "empirical" OR "data-driven" OR "multi-criteria" OR mcd* OR "machine learning" OR "deep learning" OR "artificial intelligence" OR "statistical" OR indicator* OR "index")
Publication Years (inclusive)	2010–2023	2010–2023
Disciplinary Areas	Environmental science; Earth and planetary sciences; engineering	Environmental sciences ecology; water resources; geology; engineering; oceanography; physical geography
Document Types	Article; review	Article; review
Document Language	English	English

Table 3. Articles excluded during second stage of data screening process. Criteria for spatial representation of flood adopted in this review are detailed in Section 2.2.

Criterion	**Explanation**	**Num. Articles**
Map not provided	The article does not provide a map of the coastal flood over land.	54
Unsuitable map	The article provides a map which does not conform to eligibility criteria regarding the continuity in space and link to the physical hazard or susceptibility.	55
Residual filter criterion	The article should have been eliminated in the previous phases.	47
Article unavailable	The full text of the article could not be located or retrieved.	10

After data screening, remaining articles were examined in full. A total of 18 articles were eliminated during this phase, leading to a final set of 297 articles being included in the review. Of these, 261 were related to rapid-onset coastal flooding caused by meteo-oceanic extreme events, and 36 were related to inundation caused by tsunamis. A series of data charting items (Table 4) were filled out for each article pertaining to the first category, whereas the tsunami-related literature was assessed in less detail (see Section 5.6). The reader is referred to this article's Supplementary Materials for a complete list of the reviewed articles.

Table 4. Data charting of items for articles included in review.

Data Charting Item	Retrieved Information
Methodology	Summary of the sequence of the main methodological steps performed in the analysis, mirroring the various DSPRC elements.
Models	List of model or methodology names (e.g., names of the specific hydrodynamic model used, or synthetic mention of methods, such as bathtub, MCDA, ML).
Climate Drivers/Scenarios	Specification of the use of observational data, establishment of scenarios, return times (RTs) and similar.
Compound Event	List of which drivers are being considered.
Ocean Dynamics	Name of model(s) utilised; kept empty if not modelled directly in the articles, e.g., if using pre-made datasets.
Pathway	Specification of model or methodology utilised to characterise the land–water boundary.
Type of Flood Map	E.g., flood hazard, flood vulnerability, flood risk, flood susceptibility.
Map Characteristics	Summary of the main distinguishing features of the map including scale, use of colours, use of satellite imagery, presence of multiple maps corresponding to multiple scenarios.
Vulnerability	Specification of any sub-component of vulnerability mapped in the article, if applicable.
Damage	Specification of the presence of estimates of flood damage either in monetary terms of by other means, if applicable.
Adaptation	Report of the adaptation measures proposed in the article, if applicable.
Special Focus	Specific economic sector(s) to which the flood assessment is referred to, if applicable (e.g., transport network, communication infrastructure, energy sector).
Discussion	Summary of the possible applications of the assessment presented in the article and the importance for different phases of the flood risk management process, if applicable.
Location	Location of the study area considered in the article.

2.1. The DSPRC Framework and Criteria

The Driver–Source–Pathway–Receptor–Consequence (DSPRC) [21] conceptual framework was utilised to systematise the retrieved literature and to establish some of the article selection criteria utilised throughout the literature selection process. Within the DSPRC framework, flood systems are represented as a linear succession of their individual components. Adopting this perspective allowed us in turn to systematise and streamline as much as possible both the characterisation of each component and their causal linkages, starting from the analysis of climate patterns and variation leading to the generation of extreme sea levels and moving towards the study of the consequences of coastal flooding on the socio-economic context of coastal communities [22–24]. The distinction between the different framework components is not clear-cut, and often articles can adopt quite a comprehensive approach in which multiple elements are addressed. This in turn required the studies retrieved and analysed to be attributed to multiple categories, depending on which of the framework components they focused on.

The DSPRC components are detailed below, along with the types of articles commonly focusing on them.

Driver (D): The main drivers behind the generation of sudden sea level variations in coastal areas can be either climate-related meteo-oceanic events or submarine earthquakes leading to tsunamis. Even if there might be some overlap between the two in terms of methodologies utilised to study them and research outcomes produced, the literature on tsunami-induced inundation represents a marginal interest of this literature review. A choice was made to exclude long-term SLR because of the different ranges of methodologies and policy concerns related to it when compared to rapid-onset flooding [25].

Source (S): The analysis of the source of rapid-onset coastal flooding relates to the modelling of oceanic and near-shore processes leading to the generation of extreme sea levels. Related research generally aims to estimate water level in coastal waters, often just until the water–land boundary. Articles considering fluvial-only of pluvial-only flooding in coastal areas were excluded from this review, whereas articles on compound coastal flooding were considered eligible.

Pathway (P): For rapid-onset coastal flooding, the analysis of the pathway entails addressing the passage of water from near-shore waters, through the water–land boundary, towards the inland receptor. Relevant literature examples include articles on hydrodynamic modelling and studies on the effectiveness of coastal protection infrastructure for reduction in the extent of incoming wave energy or inundation.

Receptor (R): The characterisation of the receptor requires the spatial identification of which inland portions of the coastal system might be affected by coastal flooding. Coverage of the receptor and its representation in space were considered fundamental requirements for the inclusion of articles in the review, thus excluding articles focusing exclusively on either one or a combination of the D, S, P or C components. Further criteria of the representation of the receptor were defined in terms of research outcome as detailed in Section 2.2.

Consequences (C): The estimation of the consequences of rapid-onset coastal flooding can be addressed through a multitude of disciplinary lenses, with respect to both socio-economic and natural systems. Some examples in the literature include structural appraisals of the effects of flooding on the building stock, analyses of flood-related casualties, economic damage estimation and policy-oriented research on the formulation of climate adaptation or mitigation measures.

2.2. PICOC-Related Criteria

In accordance with well-established guidelines for the development of systematic reviews, the scope of this analysis was defined in terms of which population (P), intervention (I), comparison (C), outcome (O) and context (C) (i.e., PICOC-related criteria) were to be addressed by analysed articles [16,26–28].

Population: The population comprises studies focusing on the modelling and mapping of rapid-onset flooding in coastal areas. No limitation was imposed regarding specific areas of interest; therefore, the work has a worldwide geographical scope.

Intervention: A broad range of methodologies were considered [28], including simplified and empirical models, physically based models, indicator-based models and data-driven and statistical models. Methodology-related search keywords (Table 2) were devised to be comprehensive yet generic enough to elicit a broad range of methods.

Comparison: Due to the broad scope adopted in terms of intervention, no comparison was considered.

Outcome (i.e., criteria for the spatial representation of the receptor): The articles had to portray spatial information on the receptor as a continuum in space and with some adherence to real-world physical characteristics or flood processes—for instance, the potential flood extent or the characteristics of the territory influencing susceptibility to floods. Flood maps referred to arbitrary or administrative units of space were excluded from the analysis [29].

Because of the recognised lack of clarity in the terminology related to flood risk, vulnerability and their individual components [30], as well as to keep a broad perspective on the different mapping needs required for coastal flood risk management, all the main flood-related types of maps (i.e., flood hazard, flood risk, flood vulnerability, flood susceptibility and their individual components) were considered as long as they conformed to the spatial criteria mentioned above. The spatial scale of analysis was limited to exclude flood mapping at the large scale.

Context: The reviewed studies should be aimed at providing information in support of coastal risk prevention and preparedness, with the aim of delineating coastal risk zones and informing coastal adaptation policies. Thus, articles focusing exclusively on post-event coastal flood delineation were excluded.

3. The Coastal Flood System

As mentioned before, the coastal flood system can be synthesised in a systematic way in terms of the DSPRC framework. The same framework can also be utilised to organise studies in the literature on rapid-onset coastal flooding according to the components of the flood systems that represent their main focal points.

Therefore, the reviewed studies can ideally be described according to a two-dimensional matrix, in which one dimension is based on the methodology utilised and the other regards the DSPRC components addressed. In this section, the content of reviewed studies is organised based on the different components of the considered coastal flood system, as well as combinations thereof.

3.1. Compound Coastal Flooding

Compound flooding events are particularly relevant for coastal systems because of their location at the intersection between land and sea.

For this reason, particular attention was devoted to compound coastal floods in the reviewed literature. Out of the 261 articles considering flooding caused by meteo-oceanic extreme events, 78 referred to compound coastal flooding. Compound flooding was addressed from several points of view. In some instances, the drivers and sources of flooding were the focus of the analysis. The statistical characterisation of individual flood drivers and their interrelations was the main objective of most of the articles excluded based on the *climate criterion* detailed in Table 1. Nevertheless, several of the articles included in the final reviewed set addressed to an extent the statistical characterisation of compound coastal flooding events [31–33], with some instances presenting particularly thorough analyses [34]. The high uncertainty caused by climate change-induced combined changes in individual climate drivers and in their interactions was among the most relevant issues raised by the analysed literature on compound coastal flooding, because of the disruption of the fundamental assumption of stationarity [35]. Another relevant methodological issue was that of the superposition of different flooding processes vs. the need for monolithic simulations of compound flooding events, which are required to achieve more precise results [36].

A number of studies dealt with the identification of the main flood driver within a specific area or time horizon [37]. Santiago-Collazo et al. [38] showed that the main flood mechanism within compound flood hazards (hydrologic or coastal) can change through time depending on the flood scenario considered, highlighting how the dominant flood hazard in present-day hydrologically dominated watersheds might change in future long-term predictions.

A second class of articles focused on the hydrodynamic modelling of compound coastal flooding. Often, the marine component of compound events was addressed as a boundary condition in an overland flow model, utilising observed tidal levels, estimates of overtopping volumes or the output of ocean models [31,32,39–44]. Bates et al. [45] proposed one such example, in which the combined modelling of pluvial, fluvial and coastal flooding was carried out with the LISFLOOD-FP model for present and future climates along the conterminous United States, considering the water level at the coast measured from tide gauge stations as a downstream boundary condition.

Several studies focused specifically on the characterisation of compound coastal flooding from a spatial point of view, proposing methodologies for the delineation of zones for which one flood driver may be dominant. There is general agreement that the conformation of the coast and its watersheds can play a fundamental role in the location and extent of the three hydrologic, coastal and transition zones. However, different approaches have been adopted in the literature for this purpose, and no consensus exists about the definition of the transition zone [32]. Bilskie and Hagen [46] were among the first to present a methodology for the subdivision of coastal zones based on the source of the maximum simulated water level obtained in a coupled Simulating WAves Nearshore (SWAN [47]) + ADvanced CIRCulation model (ADCIRC [48]) simulation fed with different boundary conditions. Their approach was then adopted by other reviewed articles [38,49]. In subsequent research, the transition zone was further subdivided based on the dominance of flood depth from one source over the other, such as in Wijetunge and Neluwala [50] for compound storm surge and riverine sources and in Shi et al. [51] for compound rainfall and storm surge. In the latter, the authors also proposed an overview of the literature dealing with similar mapping of coastal zones based on the dominance of different drivers. Eilander et al. [52] proposed a globally applicable modelling framework where the Super-Fast INundation of CoastS (SFINCS [53]) model was used to obtain maps showing the difference in flood depth between compound and univariate flood events for the same area. Similar approaches were also proposed in [37,54] and in [55] for an akin subdivision for a river delta system.

Yet another class of articles aimed at proposing synthetic metrics for the spatial characterisation of compound flooding in coastal areas. One such instance is the Tide–Rainfall Flood Quotient (TRFQ) metric proposed by Mohanty et al. [56], with envisioned utilisation especially by low- and medium-income countries. The TRFQ is computed based on the ratio of area flooded during design storm tide-driven flood events over that flooded for rainfall-driven flood events, and can be used as *'an incisive measure to explicate the marginal/individual contribution'* [56] of different flood drivers within coastal catchments. Shen et al. [57] introduced the Transition Zone Index (TZI), defined as the ratio of the number of simulations in which transition zones share the same location divided by the total number of simulations. Higher TZI values identify areas where flooding is likely to be the product of the interactions of storm tide and rainfall, eventually supporting the choice of suitable flood mitigation approaches.

Mitu et al. [39] proposed the use of topographic indices for the identification of areas for which a single flood driver might be most relevant.

3.2. Pathway Characterisation

The characterisation of the pathway entails the study of the coast and its structures—both natural and man-made—and the analysis of the movement of water from the sea inland. Among reviewed articles, some highlighted the generalised paucity of research on integrated atmosphere–ocean–coast–overtopping modelling [58]. Others addressed more specifically the shortcomings and complexity in the study of the movement of water from the sea, through coastal structures, towards emergent land during coastal flooding events, stressing the need to integrate tide-surge, wave and flood modelling in unified frameworks in order to accurately predict the flooding due to wave overtopping [58,59]. Some of the analysed articles presented overviews of the methodologies utilised to model the passage of water through the pathway during overtopping events and in general for coastal inundation [60,61]. In the simplest approaches utilised for this purpose, overtopping discharges are accounted for as source points in high-resolution models and then computed with empirical formulas (with the EurOtop methodology as a notable instance thereof [62]). In more complex methodologies, process-based solvers are applied in one horizontal dimension along a cross-shore transect. Le Roy et al. [60] highlighted that such empirical and 1D models are typically characterised by limits in the spatial and temporal accuracy, which might be particularly relevant in complex coastal urban areas. Finally, in the most complex methodologies—utilised in only a minority of the reviewed literature—the two horizontal dimensions are explicitly represented in the model in order to better account for the hydro- and geomorphological variability in complex coastal environments. Especially in studies applied to sea-driven inundation only, the pathway was most commonly approximated as a simple threshold between the total water level registered at the coast and the land (see Section 4.1).

Another branch of the reviewed literature approached the pathway in terms of an in-depth study of the structure of the coast itself, and of its influence on hydrodynamics in near-shore waters or within complex coastal systems such as estuaries and channels. In some instances, the main objective of the analysis was the establishment of different scenarios of coastal morphology and the study of the related variations of water dynamics, occasionally also considering combined changes in climate conditions. One such example was presented by Mansur et al. [63], in which the capacity of inland penetration of storm surge was analysed for a scenario of depth increase in a navigational channel located in an estuarine region; the authors concluded that such a modification could lead to substantial increases in inland peak water levels, peak volumetric flow rates and flooded area. Orton et al. [64] studied the influence of landscape changes (urbanisation, changes in habitats) on storm tide increase, showing the most determinant factors to be anthropogenic changes to estuary depth and inlet depth and width for their study area in New York City. Other studies [65,66] accounted for storm-related modifications to coastal morphology using the morphodynamic model XBeach [67], within numerical simulations of surge and wave conditions.

The precise representation of coastal defence structures in coastal flooding simulations for a specific location and point in time was the focus of the analysis of a number of reviewed articles [25,68]. Sometimes, advanced remote sensing techniques were utilised to precisely image such infrastructure [69]. Ke et al. [70] highlighted that few studies in the literature have explicitly considered the effects of the failure of coastal flood defences. The effects on coastal inundation of fixed protective coastal structures that were originally developed for purposes other than flood defence—such as the reclaiming of coastal wetlands—were evaluated by Christie et al. [71].

Another class of articles focused on the characterisation of coastal ecosystems and the quantification of their role as Nature-Based Solutions (NBSs) in the dampening of adverse effects of coastal inundation. Examples of NBSs that intervene in the pathway of coastal flooding are the seagrass meadows and artificial dunes considered in Unguendoli et al. [72]. Banan-Dallalian et al. [73] modelled coastal inundation caused by a tropical cyclone (TC) event with and without a hypothetical mangrove forest along the affected coastline, determining a relevant local Manning coefficient and the mangrove forest width. Results of their study showed that mangrove forests can contribute to reductions in both maximum flood depth and maximum flow velocity. Cassalho et al. [74] found that coastal wetlands can contribute to the attenuation of significant wave height as water propagates inland during storm events, even if maximum water depth is not significantly reduced. The role of foredune ridges (and erosion processes thereof) in the modification of coastal flooding processes were also analysed in the reviewed literature in an article by Danchenkov et al. [75].

3.3. Receptor

In this work, the main representation of the flood receptor has been considered the flood map, to which Section 5 is dedicated. Depending on the main objective of the study, the receptor might also be investigated more in depth, for instance, by explicitly accounting for the effects of variations in the inland coastal territory on coastal flooding. Though this type of analysis was seldom found in the analysed literature, Canters et al. [76] proposed a notable example of it. They used a cellular automata (CA) method to model variations in the land use/land cover of the study area to assess resulting variations in coastal flood risk deriving from two set scenarios of flood hazard, whereby the dynamically changing component within the flood system was the receptor.

3.4. Consequences

A significant portion of the reviewed articles analysed flood consequences, with a variety of different focuses and methodologies. For some of these, the estimation of flood-related damage was the primary objective of their analysis [77,78]. The most common approach adopted in these studies was the transformation of flood hazard information into information on flood consequences through depth–damage functions, at different levels of detail. To achieve this, some articles referenced well-established depth–damage curves such as those devised by the US Federal Emergency Management Agency (FEMA) [79]. Others formulated bespoke damage functions provided by local authorities [80], or adapted pre-existing data and functions to their study area [81].

In some instances, proper economic and damage models were utilised, such as the Delft-Fast Impact Assessment Tool (Delft-FIAT) [82], the FEMA HAZUZ platform [83] or the economic module of the Coastal Louisiana Risk Assessment (CLARA) model [84].

In some cases, spatially coarse information on land cover was utilised to characterise the type of land affected, either because of the lack of more detailed information or due to the characteristics of the receptor itself (e.g., primarily agricultural land [85]). Other studies highlighted that structural building properties are key fragility determining factors, also affecting overall flood vulnerability and related damages [86]. The need to carry out analyses at a higher level of resolution was raised, including detailed information on building age, height, configuration and construction material other than the usual depth–damage relationship [78,87].

Flood damage and economic consequences were in some cases accounted for within indicator-based methodologies. Spaulding et al. [87] formulated the Coastal Environmental Risk Index (CERI)—a methodology used to estimate expected infrastructure damage—which was also utilised in subsequent analysed publications [88]. Yan et al. [89] included sub-indicators of fiscal revenue in their assessment. Lopes et al. [90] assessed flood-related consequences within a DSPRC framework based on asset value, susceptibility and exposure, considering a wide variety of assets (*'inhabitants, land use, roads, buildings, classified areas and sensible habitats'*). Armaroli et al. [91] proposed an integrated hazard and impact modelling approach—the Integrated Disruption Assessment (INDRA)—linking numerical modelling for coastal flood hazard identification with Multiple-Criteria Decision Analysis (MCDA) to quantify direct and indirect impacts of coastal flooding based on eight standardised indicators.

A limited amount of studies addressed themes related to flood consequences in terms of environmental equity and justice, with the aim of identifying if flood impacts disproportionately affect minority, low-income or otherwise vulnerable communities. Analysed studies attained mixed results, with some examples showing that some ethnicities tend to be predominantly affected by different flood drivers (e.g., inland vs. coastal) [92] and other studies highlighting the higher relevance of socio-economic status indicators (age, gender, education) in determining disproportionate environmental inequities for flood risk when compared to ethnicity or race [93].

3.5. Addressing Multiple DSPRC Components

A limited portion of the reviewed articles proposed comprehensive studies addressing multiple DSPRC framework components, sometimes explicitly mirroring the framework structure in the study design [88]. Halsnæs et al. [94] linked climate scenarios, flood models, Geographic Information System (GIS)-based flood impact mapping and damage cost estimation, and further completed the analysis by discussing the policy implications of their research in terms of cost-effective adaptation planning for two Danish coastal urban areas. Eilander et al. [54] proposed a study of compound coastal flood risk, including univariate extreme value analysis, hazard impact modelling, damage estimation and a discussion of different adaptation and mitigation strategies based on their efficacy to address extreme events of different Return Times (RTs). Wang et al. [81] proposed a study composed of a statistical analysis of typhoon-related storm surge, numerical ocean modelling, inundation modelling with GIS, assessment of direct economic losses with depth-damage functions and a social vulnerability analysis.

Comprehensive studies able to streamline the complexity of flood processes and support risk management can represent desirable approaches. However, it is noteworthy that some reviewed of the literature cautions against the high uncertainty, errors and propagation thereof that may be embedded in outputs of complex methodology chains, which might require care in the communication and implementation of assessment results [70].

4. Methodologies to Model Rapid-Onset Coastal Flooding

Five main types of methodologies were identified in the literature to model rapid-onset coastal flooding, namely, static inundation models, raster-based approaches, index-based methodologies, data-driven methodologies and numerical methodologies. A significant portion of analysed articles utilised multiple methodologies in varying combinations, which hindered a precise estimation of the relative significance of individual classes of methodologies. At the same time, it should be acknowledged that methodologies have been aggregated in broad classes for the purpose of clarity, but that the boundaries among different methods might not be as well defined.

4.1. Static Inundation Models

Static—or "bathtub" or planar projection—models are methodologies in which all locations below a threshold water level are considered flooded, several variations of which have been proposed in the literature [95] mostly for marine-driven inundation and to a lesser extent for fluvial flooding. Static models are used mainly to obtain first approximation estimates of the potential inundation extent of flooding events because of their lower computational and data requirements compared to those of hydrodynamic or data-driven methodologies [96]. Though, they are characterised by significant drawbacks as they have been shown—with very rare exceptions [97]—to generally be less precise than process-based models and to overestimate the flood extent [98–102], because they fail to account for the physical processes underlying the flooding event and neglect the hydrological connectivity of the terrain. As highlighted by Liu et al. [103], a further differentiation can be made for the bathtub approach based on whether it is used to approximate non-source or source floods. The former are exemplified by situations of well-distributed water over a given area, such as a rainstorm over a large area where all low-lying land might be flooded. The latter describes instead a flood pulse flushing though a broken barrier such as in storm surge flooding spreading from a localised embankment break, in which case accounting for circulating conditions is even more crucial than for non-source floods.

The bathtub approach was utilised frequently in the analysed literature: 62 out of the 261 reviewed articles utilised it to some extent. The method was adopted in flood hazard studies to approximate the pathway between sea and land by projecting onto land in a relatively straightforward manner the water level obtained either from observational records or with models that solved the ocean and shallow-water hydrodynamics until the shoreline demarcation. In some of these instances [97–99,104,105], the static model was utilised as a benchmark against which to compare the performance of more complex methodologies.

The bathtub method was also utilised in studies adopting more comprehensive outlooks on coastal flood vulnerability or risk—most often utilising indicator-based methodologies (see Section 4.3)—to identify the hazard zone in a straightforward manner and then integrate such information with other socio-economic data [106–108].

Other articles focused instead on proposing some methodological improvements to the simplest form of the bathtub approach in order to address some of its limitations. For instance, Carneiro-Barros et al. [109] proposed a Tilted Bathtub Approach (TBTA) in which the relation between maximum overwash extension and the corresponding wave run-up values is more precisely defined utilising historical records of flooding for a particular location and event for validation. Enriquez et al. [96] proposed the *MatFlood* algorithm, which improves upon the conventional bathtub approach by allowing for spatially varying the water level within the water body from which the flood originates, and through the inclusion of an inverse distance reduction factor to compensate the possible overestimation of both flood extent and depth. Similar considerations of varying source water level were addressed by Breilh et al. [110], who compared different types of static inundation models (homogeneous or space-varying sea level) against a semi-dynamic method (surge overflowing method).

Attempts at introducing a measure of probability and uncertainty of inundation in static inundation models were also proposed in the reviewed literature by Fereshtehpour and Karamouz [111] and Kovanen et al. [112]. Both studies utilised probabilistic Monte Carlo approaches to generate different realisations of the terrain data within bathtub models with enforced hydrological connectivity. In the first case, the authors aimed to assess the influence of Digital Elevation Model (DEM) resolution on the inundation results. In the second study, the research objective was to obtain a *stochastic bathtub model* by generating both varying (equally probable) instances of terrain and varying instances of water level to obtain a cell-wise probability of flooding in the study area.

4.2. Other Raster-Based Approaches

Raster-based methods can represent efficient approaches in contexts where large-scale flood estimations are required at high spatial resolutions [113]. LISFLOOD-FP [114] is a widely used example of a physically based flood inundation model integrated with DEM raster data, originally designed to reduce the representation of floodplain hydraulics '*to the minimum necessary to achieve acceptable predictions*'. Though not originally developed for the study of coastal inundation, LISFLOOD-FP was extensively adopted in the reviewed literature to study both marine-driven and compound flooding in coastal areas, depending on which combinations of upstream and downstream (coastal) boundary conditions were provided to the model (e.g., [91,105,109,115–117] for marine-driven inundation and [45,118–120] for compound coastal flooding). An investigation of the influence of DEM quality and resolution on LISFLOOD-FP performance was proposed by

Seenath [121]. In some instances [37,122,123], LISFLOOD-FP was implemented as the hydrodynamic component of the integrated hydraulic and landscape evolution model CAESAR-Lisflood [124].

Makris et al. [113] proposed *CoastFLOOD*, a high-resolution *'storage-cell, mass balance flood inundation'* model, in which the problem of coastal inundation is approached as a wet/dry cell storage problem and semi-analytic hydraulic equations for continuity and volumetric flow rates are solved within a finely discretised study domain. Another raster-based inundation model for coastal inundation that solves simplified versions of shallow-water equations for each cell was also implemented by Favaretto et al. [125]. Zheng and Sun [126] proposed a similar approach that utilises principles of cellular automata (CA) to update the grid cell state.

In addition to the aforementioned process-based models closely linked to the raster data structure, other types of low-complexity raster-based flood mapping methods are also included in this section. Hydrogeomorphic classifiers based on the height above the nearest drainage (HAND; i.e., factor H) have found wide application in the literature for the rapid identification of the floodplain, most notably for inland flooding. Jafarzadegan et al. [127] noted that some adjustments are required to adapt these methods for use in coastal low-lying regions. To that end, the authors proposed a classifier similar to HAND developed specifically for coastal wetlands, estuaries and deltas, based on the distance from the nearest drainage point (i.e., factor D) as well as factor H, since factor D had been previously shown to outperform factor H in particularly flat regions.

4.3. Index-Based Methodologies

Index-based methodologies are approaches aimed at providing synthetic measures of multifaceted concepts composed by several components, such as vulnerability and risk. These methodologies generally involve the selection of which data to use as proxies of such individual components (i.e., indicators) and their aggregation into the final measure of the complex concept (i.e., index) [128].

The spatial criteria for the inclusion of articles in this review required flood maps to be presented in a spatially continuous way and to not be referred to arbitrary units of space, such as purely administrative regions. It was assumed that imposing these limitations would elicit spatialised indices retaining to a certain extent a link to the physical processes involved in flooding, by accounting for the hazard or the physical susceptibility deriving from intrinsic land characteristics. Nevertheless, the second part of the screening process (see Figure 1 and Table 3) highlighted how often articles utilising index-based methods did not meet this requirement.

This class of methodologies was most often utilised in studies proposing comprehensive assessments of vulnerability and risk to coastal flooding. From a conceptual point of view, the analysis confirmed clear conceptual confusion and lack of standardisation in the definition of these concepts and their components, with a variety of different data, aggregation techniques and miscellaneous terminology utilised in the reviewed articles. From a terminological point of view, it can be highlighted that even if some difference exists between the two, the terms index and indicator were used quite interchangeably.

The Coastal Vulnerability Index (CVI) [129,130] represents the most prevalent method in this class of reviewed literature. It is obtained as a combination of a physical vulnerability index and of a socio-economic vulnerability index, defined differently depending on the local information needs, geographic peculiarities and data availability. Mirroring this general structure, several studies utilised overlays of diverse information on natural and societal characteristics for the definition of aggregate measures of vulnerability and risk. The natural characteristics considered pertained most often to the identification of the flood hazard zone by various means such as post-event flood imagery [131], the bathtub model [56,106–108,132–134], hydrodynamic simulations [135–137] or flood hazard maps provided in previous studies or distributed as widely available data for the same area [89,138–140]. In other cases, studies considered the physical geography of the study area with data ascribable to land-related flood susceptibility factors [141–145].

The DSPRC framework was utilised in some studies to orient the choice of indicators and general methodologies utilised [89,107].

From a methodological point of view, GIS-based MCDA was commonly utilised to choose data for inclusion in the aggregate index as well as to rank the relative indicator importance, mirroring the findings of Avila-Aceves et al. [2].

4.4. Data-Driven Methodologies

Data-driven methodologies are characterised by the absence of *a priori* assumptions about the underlying functioning of a system, and are aimed at estimating functions for its approximation based on observations. This umbrella term was utilised in this review to refer to a broad lexicon utilised by individual studies, including terms such as artificial intelligence, machine learning (ML) and statistical learning.

Data-driven methodologies were used in the reviewed literature for three main purposes.

A first category of studies utilised ML to build surrogates for high-fidelity physics-based models for ocean dynamics and the inland propagation of floods [146,147]. An overview of the literature utilising ML and climate data to model ocean circulation was proposed by Pachev et al. [148] within an article utilising ML methods as a stand-in for the well-established ADCIRC. As noted by López-Lopera et al. [149], usually surrogate ML models adopt scalar representations of hydrological forcing conditions (inputs) and flood events (outputs), neglecting that inputs are time series and outputs are floods that propagate inland. To improve upon these shortcomings, they used a multioutput Gaussian process-based model that correlates functional inputs and spatial locations, which can be used with time-varying inputs and to provide information on spatially varying inland coastal flooding. ML surrogate models were also used in the analysed literature for compound coastal flooding. For instance, Bass and Bedient [150] proposed a metamodelling study of compound storm surge and rainfall-runoff, emulating ADCIRC, SWAN, the Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) and the Hydrologic Engineering Center-River Analysis System (HEC-RAS) models with the aim to predict peak inundation levels (in 2D) using hurricane landfall characteristics as inputs.

Data-driven surrogates are especially favourable in contexts that require shorter model runtimes, such as in early-warning systems (EWSs). Within this context, Chondros et al. [151] proposed an integrated methodological approach consisting of a hindcast and a forecast framework only requiring wave characteristics and sea-water-level elevation to predict maximum flood depths in areas of interest. Idier et al. [152] utilised classifier-based metamodels to estimate indicators originally computed based on the outputs of a phase-resolving numerical model (Simulating WAves till SHore (SWASH)), within a user-oriented EWS framework aimed at bridging the gap between state-of-the-art modelling and decision maker information needs.

A second class of articles utilised data-driven methodologies to assess flood susceptibility, with the aim to identify all inland areas which might be negatively affected by flood hazards because of their intrinsic characteristics. Most often the analysis was characterised as a pixel-wise supervised learning task based on the estimation of the relationship between the location of flood events (either observed or modelled) and relevant features of the territory (e.g., terrain, topography, geomorphology). The latter were usually represented as a stack of two-dimensional data covering the study area. Since most of these predictors can play a role in flooding of many different origins, the characterisation of the article as pertaining to coastal flooding for the purpose of its inclusion in the review was based mostly on the study area and the description of past flood events proposed by the authors [153–155].

The inclusion of climate-related predictors is not uncommon in studies addressing pluvial and fluvial flood susceptibility, insofar as some precipitation datasets can be easily represented in a two-dimensional way and stacked alongside other terrain-related predictors.This is not true for most climate datasets relevant for marine-driven inundation. Hasan et al. [156] included the distance from cyclone tracks among the flood susceptibility predictors; yet, the spatial interpolation for some of the other climate data utilised (e.g., mean sea level) was not explained in detail in the article.

Muñoz et al. [157] proposed a study adjacent to this category, in which a convolutional neural network (CNN) trained on satellite data and modelled flood ground truth was used along with other data fusion techniques to produce multiclass land cover classification, including classes of permanent water and floodwater.

The third class of articles utilised data-driven methodologies aimed at estimating the consequences of coastal flooding, for instance, to obtain refined exposure datasets (affected population, casualties, GDP) [158], to predict property damage [77] and total losses [80], and to predict the spatialised annual probability of flooding using data from insurance claims datasets [159].

4.5. Numerical Methodologies

Numerical methodologies are computational implementations of mathematical approximations of physical laws. They can be used in flood-related research to describe the dynamic behaviour of water with varying assumptions and simplifications depending on the scale and focus of the analysis [160].

Articles utilising numerical models represented the most prevalent class in the analysed literature. Physically based numerical models were very numerous and covered a wide array of represented process, since they can be utilised to model variable combinations of the driver, source, pathway and receptor components of the coastal flood framework. Several articles proposed diagrams representing the modelling chain of sea-driven inundation [161], showing the links and coupling between the modelling of meteorological conditions, ocean modelling—at the global, regional and local scale—and flood models for the representation of coastal inundation and the inland flood propagation.

A detailed description of all the main characteristics, data inputs and outputs, usage and limitations of the numerous numerical models used to simulate the several components of the coastal flood system is outside the scope of this work. However, a few of the reviewed articles proposed thorough portrayals of some of the models utilised to simulate coastal flooding over land. The reader is referred to Androulidakis et al. [162] for an overview of existing 2-D flood models developed for coastal inundation at various levels of complexity and to Joyce et al. [163] for a selection of 1D, 2D and 3D hydrological models. Nahon et al. [61] addressed methodologies for modelling wave overtopping discharges. Makris et al. [113] and Son et al. [40] proposed detailed lists of—respectively, and with some overlaps—flood models for coastal urban systems (including mention of required precipitation, upstream, downstream and coastal boundary conditions) and of 2D inundation model suites developed for river flooding but adapted to the study of coastal flooding.

The range of numerical models utilised in the reviewed articles extended further than those mentioned in the studies referred to above, because no limitation was established pertaining to which DSPRC components needed to be addressed by the model. Even though some ocean circulation models can also be used to model coastal inundation (e.g., ADCIRC, or the Finite-Volume Coastal Ocean Model (FVCOM) [164]), a non-negligible portion of the reviewed literature utilised numerical physically based models for the description of ocean and coastal waters (e.g., storm surge models unable to account for inundation over land such as the High-Resolution Storm Surge (HiReSS [165]) model [113] or wave models [71,120,166]), and then addressed coastal inundation with simplified methodologies (see Section 4.1) or as input to overland flow models. In articles dealing with compound coastal flooding and considering pluvial and fluvial processes, the range of methods widened further, including models for the simulation of rainfall-runoff processes to provide precipitation and upstream river boundary conditions (e.g., HEC-HMS) [43,167].

A non-negligible portion of analysed articles (approximately 9% of the articles on flooding caused by meteo-oceanic extreme events) utilised ADCIRC to simulate coastal inundation over land and to model surge and waves when coupled with the shallow-water circulation model and spectral wave model SWAN [40,168].

Matters related to model coupling within modelling chains were frequently considered in reviewed articles utilising numerical methodologies. A relevant instance thereof with regards to compound flooding was found in Bush et al. [169], in which different coupling modes for the ADCIRC and HEC-RAS models were investigated.

Another matter of importance emphasised in the reviewed literature was the definition of the spatial representation of the input coastal boundary conditions for models used to simulate coastal flooding overland: Johnson [84] highlighted how the definition of a spatially homogeneous *surge surface* from the origin water body towards land is a widely utilised and convenient abstraction that might lead in some instances to misrepresentations of the spatial development of floods.

4.6. Other Methodologies

Moradi et al. [170] used an integrated GIS and System Dynamics (SDs) model to estimate direct and indirect damage of coastal storms. Some articles utilised Bayesian Networks (BNs) for different purposes, especially to surrogate process-based models, and relate offshore hydraulic conditions to inland flood conditions and indicators of impact [171,172], or in general to represent the relationships among different elements of the coastal floodplain system [173].

Coquet et al. [174] and Elineau et al. [175] used sketch maps collected from survey respondents in coastal areas with the objective of estimating potential bias in the perception of flood risk. Sketch maps produced by respondents regarding the identification of areas potentially or previously affected by flooding were compared to the outputs of hydrodynamic modelling, showing a generalised misperception of flood risk.

5. Types of Flood Maps

The presence of a flood-related map compliant with the spatial criteria identified in Section 2.2 was a fundamental requirement for the inclusion of articles in this review. Maps of different types were featured in the analysed literature, including flood hazard, flood susceptibility, flood vulnerability, flood risk and maps of individual components of the above. The definitions of flood hazard and susceptibility maps proposed by Bentivoglio et al. [6] were adopted in this work. Because of the aforementioned lack of a standardised lexicon and methodologies for the assessment of risk and vulnerability, the classification of reviewed maps within these two categories was sometimes uncertain. As a general rule, risk maps were assumed to include information on the hazard, whereas this was not required for vulnerability maps.

The cartographic representation of the coast was among the themes analysed in the review by Bukvic et al. [176], who highlighted that no consensus exists for the delimitation of the coastal area of reference, and addressed some of the cartographic best practices that should be taken into account to communicate assessment results—in their case, specifically for coastal vulnerability mapping. Chen et al. [177] addressed cartographic best practices for hurricane evacuation maps, some of which are applicable in general to all the articles reviewed. In general, these works indicated that map products should be tailored to their context of application, sometimes also involving local stakeholders and beneficiaries of the analyses in the definition of the map characteristics depending on specific communication needs. At the same time, cartographic clarity in terms of fundamental elements such as communication of scale, use of colours and inclusion of data labels should be guaranteed.

The reviewed studies devoted varying levels of attention to the mapping product they presented depending on its role within the analysis presented. For a notable number of the reviewed articles—especially those presenting hydrodynamic simulations in the field of oceanography or engineering—the role of the flood (hazard) map within the study was mostly to support the results of the analysis, but no further utilisation was envisioned for it in terms of informing policy. This in turn is likely to be the cause of the non-compliance of these maps to cartographic guidelines mentioned above, which often complicates the interpretation of study results for outside users. Substantially different maps were proposed within articles that addressed to some extent the potential applications of the study results within the coastal flood risk management process. In these cases, proposed maps were more in line with the above guidelines, and sometimes highlighted features relevant for the definition of flood exposure and overall vulnerability.

The following sections depict the characteristics of the main map types proposed within reviewed articles.

5.1. Flood Hazard Maps

The majority of reviewed studies (241 out of the 261 articles addressing coastal floods of meteo-oceanic origin) proposed flood hazard maps, either alone or in conjunction with other types of maps. Most of the hazard maps proposed represented flood extent and depth, and to a much lesser extent, other relevant flood variables such as flood velocity [178] and time of submersion, or were maps of the time of maximum flood hazard for different portions of the coastal area considered [74]. In some instances, multiple flood hazard maps referring to different timestamps during a simulated coastal storm event were included in a time-lapse-like manner [167,179,180]. Even if some studies proposing hydrodynamic simulations mentioned that information on both flood depth and flood probability should be supplied for a complete definition of flood hazard [90], most of the studies proposing flood hazard maps did not consider probability. In some of the studies that did, the flooding probability was addressed by considering the *chance of flooding* map associated with inundation extent and maximum flood height [181], or the annual probability of areas being in the 1% flood zone [182]. A similar treatment of flooding probability embedded in hazard information was adopted by articles utilising 100-year FEMA floodplain maps. These—and similar national datasets of flood hazards—were commonly adopted as an indication of the hazard zone in studies which did not focus specifically on hazard modelling but needed an indication of it to address more comprehensive measures of risk, vulnerability or other components of the DSPRC framework [93,138]. Nevertheless, in most cases, information on the probability associated with a given flood event was conveyed through the article text but not associated to the map provided.

Most of the reviewed studies proposed flood hazard maps in which flood depth (in metres) was represented in a sequential colour scale, often associating darker blue tones to higher flood depths. Examples of diverging colour scales or colour scales based on other tones were rarer.

As addressed in more detail in Section 3.1, some articles provided maps portraying the spatial subdivision of coastal-dominated, hydrologically dominated and compound zones within the area considered [46], along with information on the flood depth.

Independent of the variable represented, flood hazard maps closely retrace the distribution of floodwater in space. These data are superimposed upon basemaps which generally vary between DEM-like greyscale backgrounds [54] and satellite imagery [91], also depending on the scale of the analysis. In rarer instances, synthetic solid-colour backgrounds [74] or stylised cartographic representations (e.g., OpenStreetMap) of coastal urban areas were utilised as basemaps.

A small proportion of articles highlighted relevant exposed assets within the map, such as important infrastructure and culturally or socially relevant locations [91,94]. It was noticed that when compared to the very symbolic representations utilised for other map types, flood hazard maps more often showed the whole study region considered and its surroundings, and provided a more specific portrayal of terrain and urban characteristics.

5.2. Flood Vulnerability Maps

According to the IPCC [183], vulnerability to a given natural hazard can be expressed as a combination of the system's exposure, sensitivity and adaptive capacity. Even though a multitude of different interpretations have been given to this concept, in general, vulnerability can further be subdivided between biophysical and socio-economic components. With regards to vulnerability to rapid-onset coastal flooding, the reviewed literature adopted a broad spectrum of interpretations, from articles focusing exclusively on biophysical vulnerability, to those considering a mix of the two components, to those considering exclusively socio-economic vulnerability [141,154]. Instances of the former approach [143] exclusively considered physical features of the area—such as land cover data [184,185] or geomorphological characteristics [142]—as a proxy for the local ability to cope with hazards. As a consequence, the spatial representation of vulnerability corresponded to the physical distribution of the geographical element which was being considered. In the latter approach, vulnerability was computed based on socio-economic indicators exclusively, and was mapped referring to spatial units that are exclusively administrative in nature. This way of representing (socio-economic) vulnerability has long been the most commonly utilised approach in the literature [186]. A middle-ground approach can consider both components of vulnerability, for which in-depth analyses can be found especially within studies focusing specifically on vulnerability and explicitly addressing the data selection and aggregation processes.

The spatial representation of vulnerability can in turn vary depending on the data aggregation strategy adopted by the individual study. In some instances [108], maps of overall vulnerability conveyed some information about the biophysical processes considered. For instance, some studies [89,186] accounted for expected flood damage computed on the base of the estimated flood depth of affected infrastructure, thus retaining spatialised flood information within the vulnerability map. A good example of this approach can be found in Rey et al. [186]. Utilising a different approach, Weis et al. [140] included information on the potential flood extent within the estimation of exposure. However, the final vulnerability map adopted the same spatial representation of sensitivity and adaptive capacity, which were based on purely administrative units.

Overall, the spatial representation of vulnerability as being referred to purely administrative units was predominant, based on the combination of *middle-ground* approaches of the latter kind with approaches considering socio-economic indicators exclusively. Regardless of the adopted approach, vulnerability was usually mapped over the study area as a dimensionless ranked index. Most analysed articles utilised five vulnerability classes and a diverging colour scale with green (or, less commonly, blue) associated with lower vulnerability and red associated with higher vulnerability. In some instances, the vulnerability map was not self-explanatory because numbered ranks were associated with colours in the map legend, without a consistent use of higher or lower numbers mirroring higher or lower vulnerability. This in turn required the reader to search for the rank explanation within the article text.

Often, flood vulnerability maps were proposed in a very stylised manner, covering the whole study region without providing information on relevant local features, terrain or on the surrounding areas outside of the study region.

5.3. Flood Risk Maps

In line with the previous relevant literature addressing the inconsistencies in the definition of the concept of risk and its operationalisation, this review highlights that no consensus emerges among analysed studies on the choice of which components to consider and how to aggregate them in a concise measure of risk. Risk was represented at times as a combination of hazard and vulnerability [136], at times as a combination of hazard, vulnerability and exposure [133], and by others considering hazard, exposure and vulnerability as well as considering a further subdivision of the latter in its physical and socio-economic components [81], to cite but a few. A thorough breakdown of the numerous different methodologies utilised for coastal flood risk assessment, as well as an analysis of the different ranking methodologies utilised for risk classification are out of the scope of this review. A focus on the differences in the spatial representation of risk that ensue from and mirror these methodological differences is adopted here. A relevant proportion of studies presenting flood risk maps did so within a broad risk analysis framework, which allowed us to compare the spatial representation of the different components of risk considered.

In general—however one defines it—flood risk is a composite indicator of natural processes (i.e., hazard) and socio-economic factors, for which different spatial representations are appropriate (see Sections 5.1 and 5.2). Depending on the individual study, risk maps can adopt the same cartographic conventions of vulnerability maps, since they are referred to the same administrative units even though they contain some form of underlying information concerning the hazard level within such boundaries [81,136]. Within a similar perspective, the spatial representation of risk can be even more abstract; for instance, in Martinelli et al. [187], risk was referred to as a series of lines parallel to the coast, for different sections of it. In fact, some of the flood risk maps proposed in the analysed articles did not conform to the spatial criteria for the selection of studies as defined in Section 2.2; these studies were included in the review exclusively on the grounds of the flood hazard maps presented in conjunction with flood risk maps. In other cases, flood risk maps veered more towards the type of spatial representation of flood hazard maps, highlighting risk within portions identified by the flood hazard [90,132,184,185,188]. Differently from flood hazard maps, flood risk maps usually represented ranked classes and not quantitative flood variables that can be represented with a continuous colour scale. For this reason, a diverging colour scale strategy similar to that described for vulnerability was commonly adopted.

5.4. Flood Susceptibility Maps

Seven of the reviewed articles proposed flood susceptibility maps. Generally, these studies were carried out with data-driven methodologies aimed at estimating the relationship between the location of past flood events and a series of predictors, commonly called flood influencing/inducing factors [153,155,156,189,190]. Eventually, all locations within the study area are classified as potentially being exposed to floods based on their intrinsic characteristics, and a continuous map of susceptibility is proposed for the study region considered. Often maps of individual predictors and maps of the flood inventory data used as ground truth were also included in the study, in addition to the final susceptibility map [22,153,155,156,189–191].

Flood susceptibility maps are obtained from and refer to purely physical features of the territory, without any additional data pertaining to socio-economic characteristics. In this sense, flood susceptibility maps more closely resemble flood hazard maps than flood vulnerability maps. Nevertheless, they share with the latter the qualitative nature of the data being represented and some of the cartographic choices mentioned before. In flood susceptibility maps, each portion of the study area is generally assigned to one of a series of qualitative classes corresponding to increasing levels of susceptibility. Susceptibility levels—usually four or five—are commonly mapped in diverging colour scale, with no general trend when it comes to the use of warmer or cooler colours for a specific end of the spectrum. It is common for studies presenting flood susceptibility assessments to map their results within a study area that is completely isolated from the broader geographical context, with no indication of the surroundings or of relevant geographical features or infrastructure in the region.

5.5. Sector-Specific Assessments

Some articles adopted a specific receptor-related perspective, dealing with an individual socio-economic sector to assess the impact and consequences of coastal flooding. Most of these works dealt with the potential impacts of coastal flooding on the transportation sector, which was mentioned to be a well-established field of research [102]. These studies aimed to identify the most critical portions of the transport infrastructure—with bridges being a prominent instance thereof—whose failure during storms and coastal flooding events might result in traffic disruptions, thus being crucial for the resiliency of the coastal system [102,192–194]. In general, this field of analysed research highlighted the need for achieving a certain level of redundancy and adaptation of the coping strategies between emergency and non-emergency measures in a dynamic way to better address the challenges of coastal flooding to the sector [192]. In an ex post analysis of the evacuation plan that had been disposed for Hurricane Irma in 2017, Huang et al. [195] highlighted that even though on that occasion the evacuation was completed successfully before the hurricane made landfall, the overestimation of the potentially affected population due to uncertainties in hurricane real-time forecasts caused traffic congestion and gasoline shortages. This work further stresses the critical importance of EWSs and information communication for the correct management of traffic during emergencies.

Flood assessments related to the transportation sector were often carried out with a combination of flood hazard modelling for the identification of the potentially flooded area with methodologies in the fields of network theory for the identification of critical nodes of the transport network. Similarly, other studies utilised alike methodologies to estimate potential disruptions and evaluate the resilience of the logistical and distribution sectors (e.g., portal infrastructure [196]) and other critical sectors (e.g., electricity systems, sewage network [197]) to coastal floods, sometimes also considering the cascade effects of disruption propagation from infrastructure and sectors directly affected by the flood to all other economic sectors within a wider area (e.g., [118] for a case study in the Caribbean island of Saint Lucia).

5.6. Tsunami-Driven Inundation

Tsunami-driven inundation constitutes a marginal interest of this review, insofar as it represents an example of rapid-onset coastal flooding which may require similar considerations in terms of both modelling, mapping and risk management. Tsunamis have historically been addressed differently the in literature when compared to other natural hazards [198], which might skew the contents of the reviewed literature. This work highlights that, for datasets identified using a search string related to coastal flood modelling and mapping (Table 2) and subsequently selected according to the data selection criteria summarised in Table 1, tsunami-related works represented only a small proportion (roughly 12%) of the final set of articles. The reader is referred to the Supplementary Materials for a list of which articles on tsunami-driven flooding were retrieved for this work, and to other relevant research (e.g., [198]) for more information on tsunami modelling.

6. Policy Implications

The issue of the function of the study in terms of its serviceability for policymaking and coastal management was actively addressed in some of the reviewed articles. While pondering the choice of appropriate tools in terms of the detail level and context-specificity of the provided information, Halsnæs et al. [94] emphasised the value of utilising localised data on flooding and costs even in light of the advantages in terms of methodological consistency of standardised methodologies or datasets. With respect to the scale of analysis utilised, Fahad et al. [78] highlighted that micro and macro assessments refer to different recipient segments, and emphasised the role and value of macro-level assessments when it comes to identifying priority regions and allocating resources. Similarly, Agharroud [106] emphasised the importance of the identification of hot spots to better define priority measures and aid in the implementation phase of coastal planning in the context of Integrated Coastal Zone Management (ICZM).

The issue of contrasting options faced during the decision making process was also addressed in studies that included different choice portfolios and master plans among the modelled scenarios considered [172]. In some studies, the authors worked specifically on tailoring the provided information to user needs. For instance, Idier et al. [152] proposed a user-oriented approach to the definition of the output of the analysis, whereby they asked what type of information was needed and then deployed a surrogate ML model to emulate indicators originally obtained as an aggregation of information from numerical models, also mentioning some of the feedback received. Other articles focused instead on the development of decision support tools (DST) such as web-based platforms for the simulation and visualisation of different scenarios of coastal flooding and adaptation [87,116,120,152].

Previous research has shown that representing and understanding complex problems and high-dimensional datasets of relevant climate variables is not straightforward [199], and this is also linked to risk perception. Interesting insights on risk perception—not necessarily only for policymakers or stakeholders, but also for the general population—were provided by [174,175], which showed a generalised underestimation of coastal flood risk in residents of coastal areas, and concluded that preventive action should take into consideration the tendency to underestimate areas exposed to flooding. On a similar note, other studies addressed the consequences of the potentially skewed risk perception on coastal management decisions: Bruno et al. [107] compared the risk of coastal floods as perceived by policymakers and stakeholders to physical risk, highlighting that risk perception can play a key role in shaping policy decisions and therefore should be taken into account to improve the effectiveness of coastal management.

The reviewed articles usually addressed the possible local adaptation measures for coastal flooding without going into too much detail about it. Those who did addressed both hazard-influencing measures and vulnerability-influencing measures [172]. The former usually entailed structural modifications of the coastal environment, and were sometimes included among the modelled scenarios considered, framing them as variations of the pathway or receptor. Variable combinations of grey and green infrastructure were proposed, such as mixes of the coastal defence structure with the replenishment of coastal ecosystems such as wetlands, vegetation and dunes [88,106,200]. Pertaining to grey infrastructure exclusively, some articles referred to the construction or modification—including retrofitting [40]—of coastal protection infrastructure such as drainage networks [41] and dikes [158]. Others focused on modifications to other types of infrastructure (e.g., the transport network [192]) to improve its resilience in the face of flooding events.

Some authors focused on green measures and the role of vegetation [25,73] or other natural features for the protection of the coast from storm events.

Coastal protection infrastructure was also addressed in terms of the assessment of the best logistical strategy to maximise its protection potential (e.g., establishing the best operating strategy for tide gates to mitigate the effects of storm surge [51]). Other articles mentioned the effectiveness of adaptation measures originally intended for another purpose; for instance, Khan et al. [201] assessed the storm surge reduction potential of land reclamation practices originally carried out in tidal zones for agricultural purposes.

A non-negligible portion of articles analysed the effects of non-structural measures [145,171] aimed at reducing vulnerability by increasing local adaptive capacity. The complexity and fragmentation of multilevel and multi-sectoral governance have been identified as relevant obstacles to the management of coastal coastal risks [107]. Within this context, multiple studies stressed the importance of establishing and maintaining communication channels among different stakeholders involved in the local coastal risk management [171], and of streamlining decision chains, reducing the responsibility fragmentation and creating integrated coastal masterplans to increase coastal safety [172].

7. Discussion and Conclusions

This review delineated the state-of-the-art of the literature regarding the modelling and mapping of rapid-onset coastal flooding, which are essential instruments for flood risk prevention and preparedness and are necessary to inform better policies for the resilience of coastal communities in the face of climate change.

Reviewed studies addressed different components of the DSPRC framework for the study of coastal flood systems, with a broad spectrum of methodologies. A generalised effort towards the development of rapid yet reliable flood assessment methodologies was noticed regardless of the disciplinary field, aimed especially to support flood EWSs and emergency responses.

The high level of uncertainty caused by the simplifications that are necessary to quantify the vulnerability of human and natural assets was among the most recurrent study limitations discussed by authors [82]. On a similar note, multiple studies emphasised the uncertainty embedded in well-established and widely used flood hazard and damage datasets, which might be particularly relevant for some coastal areas and lead to the underestimation of flood risk [36,44,159,202]. Issues pertaining to data availability and quality are of particular relevance for flood research [45] and were reported by numerous reviewed articles and across a broad range of geographical areas. This was observed for all types of data considered in the literature, including topographic and bathymetric datasets, observational wind and pressure fields—especially relevant for some particularly affected areas such as the Bay of Bengal [201,203]—and data needed for the characterisation of exposure such as census and infrastructure data [78,158].

Previous research emphasised the shortcomings in the description of the complex relationships among hydrodynamics, structural characteristics and community preparedness that determine the overall resilience of a community to floods [78]. Therefore, this review combined a broad scope in terms of adopted methodologies with stricter criteria for the type of spatial representation of floods to review studies conveying some level of information about the natural flooding processes, along with the local socio-economic indicators that are most commonly represented in the literature dealing with flood vulnerability and risk [186].

The results of this work highlighted that most of the articles selected based on these criteria focused exclusively on flood hazard, while only a residual portion of the analysed literature adopted broader perspectives encompassing flood vulnerability, risk and susceptibility. Even though different research products might be required to support different phases of the risk management process and diverse localised needs [78,202], the findings of this study emphasised the generalised lack of integration between studies focusing on the natural processes leading to flooding and those addressing the socio-economic characteristics contributing to vulnerability. On a related note, this review substantiated findings of extensive previous research on inconsistencies in the definition and operationalisation of most of the basic concepts related to the relationship between human and natural systems in the context of natural hazards. The unclear definitions of risk and vulnerability found a corresponding inconsistent translation in their spatial representation; this may require that these issues be more carefully addressed by the scientific community as they can represent a hindrance to an accessible application of research outputs to support climate adaptation policies.

The findings of this systematic review point to several promising directions for future research in coastal flood modelling and mapping. Future research efforts should focus on improving the representation of feedback mechanisms among the different components of a coastal flood system. This includes investigations pertaining to the relationship between different—potentially compound—coastal flooding sources and morphological changes, particularly in urban environments. Another relevant aspect to be studied in this area relates to the more accurate representation of the morphology of natural and man-made coastal structures in hydrodynamic models, and the quantification of uncertainty in the possible propagation of water inland.

Further attention is required to translate scientific advances into operational flood forecasting systems. The challenges of translating scientific research results into practical policy actions analysed in this paper relate specifically to climate change adaptation and resilience policies in coastal zones. However, the same challenges can be found at the research–policy interface more generally. The literature on this topic [204] has identified issues such as fragmentation in knowledge generation and sharing, more effective communication of research through face-to-face interactions between researchers and policy-makers, and the existence of trusting relationships between the two as some of the main reasons for these communication and practical difficulties. Future research developments could focus on the other complementary aspect of the research presented here, i.e., how different modelling and mapping results are used in practice from a policy perspective. On this note, focusing on the spatial representation of floods and other climate-related stressors is closely linked to the utilisation of vulnerability assessments for policies or practices envisioned by researchers, though the actual uptake of such assessments by practitioners remains an open question, as highlighted in previous research [205]. The role of local communities, policymakers or other stakeholders in utilizing flood maps is another fundamental aspect of research that might require investigation in future research. Therefore, future research should address the development of robust uncertainty quantification methods suitable for operational implementation, including the communication of these uncertainties to end-users. Finally, the standardization of flood mapping products and modelling approaches represents an important direction for future work. This includes evaluating the development of widely accepted protocols for model validation and uncertainty communication and standardised methods for incorporating new data sources and modelling techniques into existing flood risk assessment frameworks.

Supplementary Materials: The following supporting information can be downloaded at: https://doi.org/10.5281/zenodo.14599407.

Author Contributions: Conceptualization, A.R.; methodology, A.R.; software, A.R.; validation, A.R., L.M. and A.P.; formal analysis, A.R., L.M. and A.P.; investigation, A.R.; data curation, A.R., L.M. and A.P.; writing—original draft preparation, A.R.; writing—review and editing, A.R., L.M. and A.P.; supervision, L.M. and A.P. All authors have read and agreed to the published version of the manuscript.

Funding: Lorenzo Minola was funded by the International Postdoc grant from the Swedish Research Council (2021-00444).

Data Availability Statement: The original contributions presented in this study are included in the article/Supplementary Materials. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Green, J.; Haigh, I.; Quinn, N.; Neal, J.; Wahl, T.; Wood, M.; Eilander, D.; de Ruiter, M.; Ward, P.; Camus, P. Review Article: A Comprehensive Review of Compound Flooding Literature with a Focus on Coastal and Estuarine Regions. *EGUsphere* **2024**, *2024*, 1–108. [CrossRef]
2. Avila-Aceves, E.; Plata-Rocha, W.; Monjardin-Armenta, S.A.; Rangel-Peraza, J.G. Geospatial modelling of floods: A literature review. *Stoch. Environ. Res. Risk Assess.* **2023**, *37*, 4109–4128. [CrossRef]
3. Cea, L.; Costabile, P. Flood Risk in Urban Areas: Modelling, Management and Adaptation to Climate Change. A Review. *Hydrology* **2022**, *9*, 50. [CrossRef]
4. Reinwald, F.; Thiel, S.; Kainz, A.; Hahn, C. Components of urban climate analyses for the development of planning recommendation maps. *Urban Clim.* **2024**, *57*, 102090. [CrossRef]
5. Teng, J.; Jakeman, A.; Vaze, J.; Croke, B.; Dutta, D.; Kim, S. Flood inundation modelling: A review of methods, recent advances and uncertainty analysis. *Environ. Model. Softw.* **2017**, *90*, 201–216. [CrossRef]
6. Bentivoglio, R.; Isufi, E.; Jonkman, S.N.; Taormina, R. Deep learning methods for flood mapping: A review of existing applications and future research directions. *Hydrol. Earth Syst. Sci.* **2022**, *26*, 4345–4378. [CrossRef]
7. Ferreira, Ó.; Plomaritis, T.A.; Costas, S. Process-based indicators to assess storm induced coastal hazards. *Earth-Sci. Rev.* **2017**, *173*, 159–167. [CrossRef]
8. Gallien, T.W.; Kalligeris, N.; Delisle, M.P.C.; Tang, B.X.; Lucey, J.T.D.; Winters, M.A. Coastal Flood Modeling Challenges in Defended Urban Backshores. *Geosciences* **2018**, *8*, 450. [CrossRef]
9. Santiago-Collazo, F.L.; Bilskie, M.V.; Hagen, S.C. A comprehensive review of compound inundation models in low-gradient coastal watersheds. *Environ. Model. Softw.* **2019**, *119*, 166–181. [CrossRef]
10. Mudashiru, R.B.; Sabtu, N.; Abustan, I. Quantitative and semi-quantitative methods in flood hazard/susceptibility mapping: A review. *Arab. J. Geosci.* **2021**, *14*, 941. [CrossRef]
11. Mudashiru, R.B.; Sabtu, N.; Abustan, I.; Balogun, W. Flood hazard mapping methods: A review. *J. Hydrol.* **2021**, *603*, 126846. [CrossRef]
12. Batista, C.M. Coastal Flood Hazard Mapping. In *Encyclopedia of Coastal Science*; Finkl, C.W., Makowski, C., Eds.; Springer International Publishing: Cham, Switzerland, 2018; pp. 1–11. [CrossRef]
13. Vousdoukas, M.I.; Voukouvalas, E.; Mentaschi, L.; Dottori, F.; Giardino, A.; Bouziotas, D.; Bianchi, A.; Salamon, P.; Feyen, L. Developments in large-scale coastal flood hazard mapping. *Nat. Hazards Earth Syst. Sci.* **2016**, *16*, 1841–1853. [CrossRef]
14. Arksey, H.; O'Malley, L. Scoping studies: Towards a methodological framework. *Int. J. Soc. Res. Methodol.* **2005**, *8*, 19–32. [CrossRef]

15. Levac, D.; Colquhoun, H.; O'Brien, K.K. Scoping studies: Advancing the methodology. *Implement. Sci.* **2010**, *5*, 1–9. [CrossRef]
16. Aromataris, E.; Munn, Z. (Eds.) *JBI Manual for Evidence Synthesis*; JBI: Miami, FL, USA, 2020. [CrossRef]
17. Lima, C.O.; Bonetti, J. Bibliometric analysis of the scientific production on coastal communities' social vulnerability to climate change and to the impact of extreme events. *Nat. Hazards* **2020**, *102*, 1589–1610. [CrossRef]
18. Bosserelle, A.L.; Morgan, L.K.; Hughes, M.W. Groundwater Rise and Associated Flooding in Coastal Settlements Due To Sea-Level Rise: A Review of Processes and Methods. *Earth's Future* **2022**, *10*, e2021EF002580. [CrossRef]
19. Ankrah, J.; Monteiro, A.; Madureira, H. Geospatiality of sea level rise impacts and communities' adaptation: A bibliometric analysis and systematic review. *Nat. Hazards* **2023**, *116*, 1–31. [CrossRef]
20. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef] [PubMed]
21. Holdgate, M.W. *A Perspective of Environmental Pollution*; Cambridge University Press: Cambridge, UK, 1979.
22. Fang, X.; Zhang, Y.; Xiang, Y.; Zou, J.; Li, X.; Hao, C.; Wang, J. A spatial model for coastal flood susceptibility assessment using the 2D-SPR method with complex network theory: A case study of a reclamation island in Zhoushan, China. *Environ. Impact Assess. Rev.* **2023**, *98*, 106953. [CrossRef]
23. Zanuttigh, B. Coastal flood protection: What perspective in a changing climate? The THESEUS approach. *Environ. Sci. Policy* **2011**, *14*, 845–863. [CrossRef]
24. Evans, E.; Hall, J.; Penning-Rowsell, E.; Sayers, P.; Thorne, C.; Watkinson, A. Future flood risk management in the UK. *Proc. Inst. Civ. Eng.—Water Manag.* **2006**, *159*, 53–61. [CrossRef]
25. Croteau, R.; Pacheco, A.; Ferreira, Ó. Flood vulnerability under sea level rise for a coastal community located in a backbarrier environment, Portugal. *J. Coast. Conserv.* **2023**, *27*, 28. [CrossRef]
26. Petersen, K.; Vakkalanka, S.; Kuzniarz, L. Guidelines for conducting systematic mapping studies in software engineering: An update. *Inf. Softw. Technol.* **2015**, *64*, 1–18. [CrossRef]
27. Carrera-Rivera, A.; Ochoa, W.; Larrinaga, F.; Lasa, G. How-to conduct a systematic literature review: A quick guide for computer science research. *MethodsX* **2022**, *9*, 101895. [CrossRef]
28. Wohlin, C.; Runeson, P.; Höst, M.; Ohlsson, M.C.; Regnell, B.; Wesslén, A. *Experimentation in Software Engineering*; Springer: Berlin/Heidelberg, Germany, 2012. [CrossRef]
29. Re, A.; Minola, L.; Pezzoli, A. Climate Scenarios for Coastal Flood Vulnerability Assessments: A Case Study for the Ligurian Coastal Region. *Climate* **2023**, *11*, 56. [CrossRef]
30. Bigi, V.; Comino, E.; Fontana, M.; Pezzoli, A.; Rosso, M. Flood Vulnerability Analysis in Urban Context: A Socioeconomic Sub-Indicators Overview. *Climate* **2021**, *9*, 12. [CrossRef]
31. Gao, L.; Du, H.; Huang, H.; Zhang, L.; Zhang, P. Modelling the compound floods upon combined rainfall and storm surge events in a low-lying coastal city. *J. Hydrol.* **2023**, *627*, 130476. [CrossRef]
32. Gori, A.; Lin, N.; Xi, D. Tropical Cyclone Compound Flood Hazard Assessment: From Investigating Drivers to Quantifying Extreme Water Levels. *Earth's Future* **2020**, *8*, e2020EF001660. [CrossRef]
33. Moftakhari, H.; Schubert, J.E.; AghaKouchak, A.; Matthew, R.A.; Sanders, B.F. Linking statistical and hydrodynamic modeling for compound flood hazard assessment in tidal channels and estuaries. *Adv. Water Resour.* **2019**, *128*, 28–38. [CrossRef]
34. Olbert, A.I.; Moradian, S.; Nash, S.; Comer, J.; Kazmierczak, B.; Falconer, R.A.; Hartnett, M. Combined statistical and hydrodynamic modelling of compound flooding in coastal areas—Methodology and application. *J. Hydrol.* **2023**, *620*, 129383. [CrossRef]
35. Wang, H.; Xuan, Y.; Tran, T.V.T.; Couasnon, A.; Scussolini, P.; Luu, L.N.; Nguyen, H.Q.; Reeve, D.E. Changes in seasonal compound floods in Vietnam revealed by a time-varying dependence structure of extreme rainfall and high surge. *Coast. Eng.* **2023**, *183*, 104330. [CrossRef]
36. Stephens, T.A.; Savant, G.; Sanborn, S.C.; Wallen, C.M.; Roy, S. Monolithic Multiphisics Simulation of Compound Flooding. *J. Hydraul. Eng.* **2022**, *148*, 05022003. [CrossRef]
37. Harrison, L.M.; Coulthard, T.J.; Robins, P.E.; Lewis, M.J. Sensitivity of Estuaries to Compound Flooding. *Estuaries Coasts* **2022**, *45*, 1250–1269. [CrossRef]
38. Santiago-Collazo, F.L.; Bilskie, M.B.; Bacopoulos, P.; Hagen, S.C. An examination of compound flood hazard zones for past, present and future low-gradient coastal land-margins. *Front. Clim.* **2021**, *3*, 684035. [CrossRef]
39. Mitu, M.F.; Sofia, G.; Shen, X.; Anagnostou, E.N. Assessing the compound flood risk in coastal areas: Framework formulation and demonstration. *J. Hydrol.* **2023**, *626*, 130278. [CrossRef]
40. Son, Y.; Di Lorenzo, E.; Luo, J. WRF-Hydro-CUFA: A scalable and adaptable coastal-urban flood model based on the WRF-Hydro and SWMM models. *Environ. Model. Softw.* **2023**, *167*, 105770. [CrossRef]
41. Long, Z.Y.; Gao, L. Estimating the combined risks of sea level rise and storm surges using a numerical model: Application to Macao. *J. Clean. Prod.* **2023**, *407*, 137155. [CrossRef]

42. Muñoz, D.F.; Abbaszadeh, P.; Moftakhari, H.; Moradkhani, H. Accounting for uncertainties in compound flood hazard assessment: The value of data assimilation. *Coast. Eng.* **2022**, *171*, 104057. [CrossRef]
43. Wang, S.; Najafi, M.R.; Cannon, A.J.; Khan, A.A. Uncertainties in Riverine and Coastal Flood Impacts under Climate Change. *Water* **2021**, *13*, 1774. [CrossRef]
44. Khanam, M.; Sofia, G.; Koukoula, M.; Lazin, R.; Nikolopoulos, E.I.; Shen, X.; Anagnostou, E.N. Impact of compound flood event on coastal critical infrastructures considering current and future climate. *Nat. Hazards Earth Syst. Sci.* **2021**, *21*, 587–605. [CrossRef]
45. Bates, P.D.; Quinn, N.; Sampson, C.; Smith, A.; Wing, O.; Sosa, J.; Savage, J.; Olcese, G.; Neal, J.; Schumann, G.; et al. Combined Modeling of US Fluvial, Pluvial, and Coastal Flood Hazard Under Current and Future Climates. *Water Resour. Res.* **2021**, *57*, e2020WR028673. [CrossRef]
46. Bilskie, M.V.; Hagen, S.C. Defining Flood Zone Transitions in Low-Gradient Coastal Regions. *Geophys. Res. Lett.* **2018**, *45*, 2761–2770. [CrossRef]
47. Booij, N.; Ris, R.C.; Holthuijsen, L.H. A third-generation wave model for coastal regions: 1. Model description and validation. *J. Geophys. Res. Ocean.* **1999**, *104*, 7649–7666. [CrossRef]
48. Luettich, R.A.; Westerink, J.J. *Formulation and Numerical Implementation of the 2D/3D ADCIRC Finite Element Model Version 44. XX*; R. Luettich: Chapel Hill, NC, USA, 2004; Volume 20.
49. Bilskie, M.V.; Zhao, H.; Resio, D.; Atkinson, J.; Cobell, Z.; Hagen, S.C. Enhancing Flood Hazard Assessments in Coastal Louisiana Through Coupled Hydrologic and Surge Processes. *Front. Water* **2021**, *3*, 609231. [CrossRef]
50. Wijetunge, J.J.; Neluwala, N.G.P.B. Compound flood hazard assessment and analysis due to tropical cyclone-induced storm surges, waves and precipitation: A case study for coastal lowlands of Kelani river basin in Sri Lanka. *Nat. Hazards* **2023**, *116*, 3979–4007. [CrossRef]
51. Shi, S.; Yang, B.; Jiang, W. Numerical simulations of compound flooding caused by storm surge and heavy rain with the presence of urban drainage system, coastal dam and tide gates: A case study of Xiangshan, China. *Coast. Eng.* **2022**, *172*, 104064. [CrossRef]
52. Eilander, D.; Couasnon, A.; Leijnse, T.; Ikeuchi, H.; Yamazaki, D.; Muis, S.; Dullaart, J.; Haag, A.; Winsemius, H.C.; Ward, P.J. A globally applicable framework for compound flood hazard modeling. *Nat. Hazards Earth Syst. Sci.* **2023**, *23*, 823–846. [CrossRef]
53. Leijnse, T.; van Ormondt, M.; Nederhoff, K.; van Dongeren, A. Modeling compound flooding in coastal systems using a computationally efficient reduced-physics solver: Including fluvial, pluvial, tidal, wind- and wave-driven processes. *Coast. Eng.* **2021**, *163*, 103796. [CrossRef]
54. Eilander, D.; Couasnon, A.; Sperna Weiland, F.C.; Ligtvoet, W.; Bouwman, A.; Winsemius, H.C.; Ward, P.J. Modeling compound flood risk and risk reduction using a globally applicable framework: A pilot in the Sofala province of Mozambique. *Nat. Hazards Earth Syst. Sci.* **2023**, *23*, 2251–2272. [CrossRef]
55. Sampurno, J.; Vallaeys, V.; Ardianto, R.; Hanert, E. Modeling interactions between tides, storm surges, and river discharges in the Kapuas River delta. *Biogeosciences* **2022**, *19*, 2741–2757. [CrossRef]
56. Mohanty, M.P.; Sherly, M.A.; Ghosh, S.; Karmakar, S. Tide-rainfall flood quotient: An incisive measure of comprehending a region's response to storm-tide and pluvial flooding. *Environ. Res. Lett.* **2020**, *15*, 064029. [CrossRef]
57. Shen, Y.; Morsy, M.M.; Huxley, C.; Tahvildari, N.; Goodall, J.L. Flood risk assessment and increased resilience for coastal urban watersheds under the combined impact of storm tide and heavy rainfall. *J. Hydrol.* **2019**, *579*, 124159. [CrossRef]
58. Xie, D.; Zou, Q.P.; Mignone, A.; MacRae, J.D. Coastal flooding from wave overtopping and sea level rise adaptation in the northeastern USA. *Coast. Eng.* **2019**, *150*, 39–58. [CrossRef]
59. Suh, S.W.; Lee, M.H. Analysis of Typhoon-Induced Wave Overtopping Vulnerability Due to Sea Level Rise Using a Coastal–Seawall–Terrestrial Seamless Grid System. *J. Mar. Sci. Eng.* **2023**, *11*, 2114. [CrossRef]
60. Le Roy, S.; Pedreros, R.; André, C.; Paris, F.; Lecacheux, S.; Marche, F.; Vinchon, C. Coastal flooding of urban areas by overtopping: Dynamic modelling application to the Johanna storm (2008) in Gâvres (France). *Nat. Hazards Earth Syst. Sci.* **2015**, *15*, 2497–2510. [CrossRef]
61. Nahon, A.; Fortunato, A.B.; Oliveira, F.S.; Azevedo, A.; Henriques, M.J.; Silva, P.A.; Baptista, P.; Freire, P. 2DH modelling and mapping of surfbeat-driven flooding in the shadow of a jettied tidal inlet. *Coast. Eng.* **2023**, *184*, 104342. [CrossRef]
62. Van der Meer, J.W.; Allsop, N.W.H.; Bruce, T.; De Rouck, J.; Kortenhaus, A.; Pullen, T.; Schüttrumpf, H.; Troch, P.; Zanuttigh, B. EurOtop, 2018. Manual on Wave Overtopping of Sea Defences and Related Structures. An Overtopping Manual Largely Based on European Research, but for Worldwide Application. Available online: https://www.overtopping-manual.com (accessed on 13 February 2025).
63. Mansur, M.; Hopkins, J.; Chen, Q. Estuarine response to storm surge and sea-level rise associated with channel deepening: A flood vulnerability assessment of southwest Louisiana, USA. *Nat. Hazards* **2023**, *116*, 3879–3897. [CrossRef]
64. Orton, P.M.; Sanderson, E.W.; Talke, S.A.; Giampieri, M.; MacManus, K. Storm tide amplification and habitat changes due to urbanization of a lagoonal estuary. *Nat. Hazards Earth Syst. Sci.* **2020**, *20*, 2415–2432. [CrossRef]

65. Frey, A.E.; Olivera, F.; Irish, J.L.; Dunkin, L.M.; Kaihatu, J.M.; Ferreira, C.M.; Edge, B.L. Potential Impact of Climate Change on Hurricane Flooding Inundation, Population Affected and Property Damages in Corpus Christi. *J. Am. Water Resour. Assoc.* **2010**, *46*, 1049–1059. [CrossRef]
66. Grilli, A.R.; Westcott, G.; Grilli, S.T.; Spaulding, M.L.; Shi, F.; Kirby, J.T. Assessing coastal hazard from extreme storms with a phase resolving wave model: Case study of Narragansett, RI, USA. *Coast. Eng.* **2020**, *160*, 103735. [CrossRef]
67. Roelvink, D.; Reniers, A.; Van Dongeren, A.; Van Thiel de Vries, J.; Lescinski, J.; McCall, R. *XBeach Model Description and Manual*; Report June; Unesco-IHE Institute for Water Education, Deltares and Delft University of Tecnhology: Delft, The Netherlands, 2010; Volume 21.
68. Kiesel, J.; Honsel, L.E.; Lorenz, M.; Gräwe, U.; Vafeidis, A.T. Raising dikes and managed realignment may be insufficient for maintaining current flood risk along the German Baltic Sea coast. *Commun. Earth Environ.* **2023**, *4*, 433. [CrossRef]
69. Gallien, T.W.; Barnard, P.L.; van Ormondt, M.; Foxgrover, A.C.; Sanders, B.F. A Parcel-Scale Coastal Flood Forecasting Prototype for a Southern California Urbanized Embayment. *J. Coast. Res.* **2013**, *29*, 642–656. [CrossRef]
70. Ke, Q.; Yin, J.; Bricker, J.D.; Savage, N.; Buonomo, E.; Ye, Q.; Visser, P.; Dong, G.; Wang, S.; Tian, Z.; et al. An integrated framework of coastal flood modelling under the failures of sea dikes: A case study in Shanghai. *Nat. Hazards* **2021**, *109*, 671–703. [CrossRef]
71. Christie, E.K.; Spencer, T.; Pollard, J.A.; Brooks, S.M.; Palaima, A. Evaluating the viability of coastal wet grassland to a changing management regime through flood hazard modelling. *Ecol. Eng.* **2020**, *158*, 106020. [CrossRef]
72. Unguendoli, S.; Biolchi, L.G.; Aguzzi, M.; Pillai, U.P.A.; Alessandri, J.; Valentini, A. A modeling application of integrated nature based solutions (NBS) for coastal erosion and flooding mitigation in the Emilia-Romagna coastline (Northeast Italy). *Sci. Total. Environ.* **2023**, *867*, 161357. [CrossRef] [PubMed]
73. Banan-Dallalian, M.; Shokatian-Beiragh, M.; Golshani, A.; Mojtahedi, A.; Lotfollahi-Yaghin, M.A.; Akib, S. Study of the Effect of an Environmentally Friendly Flood Risk Reduction Approach on the Oman Coastlines during the Gonu Tropical Cyclone (Case Study: The Coastline of Sur). *Eng* **2021**, *2*, 141–155. [CrossRef]
74. Cassalho, F.; Miesse, T.W.; de Lima, A.d.S.; Khalid, A.; Ferreira, C.M.; Sutton-Grier, A.E. Coastal Wetlands Exposure to Storm Surge and Waves in the Albemarle-Pamlico Estuarine System during Extreme Events. *Wetlands* **2021**, *41*, 49. [CrossRef]
75. Danchenkov, A.; Belov, N.; Bubnova, E.; Myslenkov, S. Foredune defending role: Vulnerability and potential risk through combined satellite and hydrodynamics approach. *Remote Sens. Appl. Soc. Environ.* **2023**, *30*, 100934. [CrossRef]
76. Canters, F.; Vanderhaegen, S.; Khan, A.Z.; Engelen, G.; Uljee, I. Land-use simulation as a supporting tool for flood risk assessment and coastal safety planning: The case of the Belgian coast. *Ocean. Coast. Manag.* **2014**, *101*, 102–113. [CrossRef]
77. Museru, M.L.; Nazari, R.; Giglou, A.N.; Opare, K.; Karimi, M. Advancing flood damage modeling for coastal Alabama residential properties: A multivariable machine learning approach. *Sci. Total. Environ.* **2024**, *907*, 167872. [CrossRef] [PubMed]
78. Fahad, M.G.R.; Nazari, R.; Motamedi, M.; Karimi, M. A Decision-Making Framework Integrating Fluid and Solid Systems to Assess Resilience of Coastal Communities Experiencing Extreme Storm Events. *Reliab. Eng. Syst. Saf.* **2022**, *221*, 108388. [CrossRef]
79. Sebastian, A.; Bader, D.J.; Nederhoff, C.M.; Leijnse, T.W.B.; Bricker, J.D.; Aarninkhof, S.G.J. Hindcast of pluvial, fluvial, and coastal flood damage in Houston, Texas during Hurricane Harvey (2017) using SFINCS. *Nat. Hazards* **2021**, *109*, 2343–2362. [CrossRef]
80. Hisamatsu, R.; Tabeta, S.; Kim, S.; Mizuno, K. Storm surge risk assessment for the insurance system: A case study in Tokyo Bay, Japan. *Ocean. Coast. Manag.* **2020**, *189*, 105147. [CrossRef]
81. Wang, S.; Mu, L.; Qin, H.; Wang, L.; Yao, Z.; Zhao, E. The utilization of physically based models and GIS techniques for comprehensive risk assessment of storm surge: A case study of Huizhou. *Front. Mar. Sci.* **2022**, *9*, 939380. [CrossRef]
82. Parodi, M.U.; Giardino, A.; van Dongeren, A.; Pearson, S.G.; Bricker, J.D.; Reniers, A.J.H.M. Uncertainties in coastal flood risk assessments in small island developing states. *Nat. Hazards Earth Syst. Sci.* **2020**, *20*, 2397–2414. [CrossRef]
83. Karamouz, M.; Fereshtehpour, M.; Ahmadvand, F.; Zahmatkesh, Z. Coastal Flood Damage Estimator: An Alternative to FEMA's HAZUS Platform. *J. Irrig. Drain. Eng.* **2016**, *142*, 04016016. [CrossRef]
84. Johnson, D.R. Improved Methods for Estimating Flood Depth Exceedances Within Storm Surge Protection Systems. *Risk Anal.* **2019**, *39*, 890–905. [CrossRef]
85. Islam, M.F.; Bhattacharya, B.; Popescu, I. Flood risk assessment due to cyclone-induced dike breaching in coastal areas of Bangladesh. *Nat. Hazards Earth Syst. Sci.* **2019**, *19*, 353–368. [CrossRef]
86. Ding, Z.; Zhang, W.; Hughes, W.; Zhu, D. A modified sub-assembly approach for hurricane induced wind-surge-wave vulnerability assessment of low-rise wood buildings in coastal communities. *J. Wind. Eng. Ind. Aerodyn.* **2021**, *218*, 104755. [CrossRef]
87. Spaulding, M.L.; Grilli, A.; Damon, C.; Crean, T.; Fugate, G.; Oakley, B.A.; Stempel, P. STORMTOOLS: Coastal Environmental Risk Index (CERI). *J. Mar. Sci. Eng.* **2016**, *4*, 54. [CrossRef]
88. Grilli, A.; Spaulding, M.L.; Oakley, B.A.; Damon, C. Mapping the coastal risk for the next century, including sea level rise and changes in the coastline: Application to Charlestown RI, USA. *Nat. Hazards* **2017**, *88*, 389–414. [CrossRef]

89. Yan, B.; Wang, J.; Li, S.; Cui, L.; Ge, Z.; Zhang, L. Assessment of socio-economic vulnerability under sea level rise coupled with storm surge in the Chongming County, Shanghai. *Acta Ecol. Sin.* **2016**, *36*, 91–98. [CrossRef]
90. Lopes, C.L.; Alves, F.L.; Dias, J.M. Flood risk assessment in a coastal lagoon under present and future scenarios: Ria de Aveiro case study. *Nat. Hazards* **2017**, *89*, 1307–1325. [CrossRef]
91. Armaroli, C.; Duo, E.; Viavattene, C. From Hazard to Consequences: Evaluation of Direct and Indirect Impacts of Flooding Along the Emilia-Romagna Coastline, Italy. *Front. Earth Sci.* **2019**, *7*, 203. [CrossRef]
92. Montgomery, M.C.; Chakraborty, J. Assessing the environmental justice consequences of flood risk: A case study in Miami, Florida. *Environ. Res. Lett.* **2015**, *10*, 095010. [CrossRef]
93. Mazumder, L.T.; Landry, S.; Alsharif, K. Coastal cities in the Southern US floodplains: An evaluation of environmental equity of flood hazards and social vulnerabilities. *Appl. Geogr.* **2022**, *138*, 102627. [CrossRef]
94. Halsnæs, K.; Larsen, M.A.D.; Sunding, T.P.; Dømgaard, M.L. The value of advanced flood models, damage costs and land use data in cost-effective climate change adaptation. *Clim. Serv.* **2023**, *32*, 100424. [CrossRef]
95. Williams, L.L.; Lück-Vogel, M. Comparative assessment of the GIS based bathtub model and an enhanced bathtub model for coastal inundation. *J. Coast. Conserv.* **2020**, *24*, 23. [CrossRef]
96. Enriquez, A.R.; Wahl, T.; Talke, S.A.; Orton, P.M.; Booth, J.F.; Agulles, M.; Santamaria-Aguilar, S. MatFlood: An efficient algorithm for mapping flood extent and depth. *Environ. Model. Softw.* **2023**, *169*, 105829. [CrossRef]
97. Didier, D.; Baudry, J.; Bernatchez, P.; Dumont, D.; Sadegh, M.; Bismuth, E.; Bandet, M.; Dugas, S.; Sévigny, C. Multihazard simulation for coastal flood mapping: Bathtub versus numerical modelling in an open estuary, Eastern Canada. *J. Flood Risk Manag.* **2019**, *12*, e12505. [CrossRef]
98. Gallien, T.; Schubert, J.; Sanders, B. Predicting tidal flooding of urbanized embayments: A modeling framework and data requirements. *Coast. Eng.* **2011**, *58*, 567–577. [CrossRef]
99. Gallien, T.; Sanders, B.; Flick, R. Urban coastal flood prediction: Integrating wave overtopping, flood defenses and drainage. *Coast. Eng.* **2014**, *91*, 18–28. [CrossRef]
100. Ramirez, J.A.; Lichter, M.; Coulthard, T.J.; Skinner, C. Hyper-resolution mapping of regional storm surge and tide flooding: Comparison of static and dynamic models. *Nat. Hazards* **2016**, *82*, 571–590. [CrossRef]
101. Rey, W.; Ruiz-Salcines, P.; Salles, P.; Urbano-Latorre, C.P.; Escobar-Olaya, G.; Osorio, A.F.; Ramírez, J.P.; Cabarcas-Mier, A.; Jigena-Antelo, B.; Appendini, C.M. Hurricane Flood Hazard Assessment for the Archipelago of San Andres, Providencia and Santa Catalina, Colombia. *Front. Mar. Sci.* **2021**, *8*, 766258. [CrossRef]
102. Tahvildari, N.; Castrucci, L. Relative Sea Level Rise Impacts on Storm Surge Flooding of Transportation Infrastructure. *Nat. Hazards Rev.* **2021**, *22*, 04020045. [CrossRef]
103. Liu, Y.; Li, S.; Wang, Z. Assessment of Storm Surge and Flood Inundation in Chittagong City of Bangladesh Based on ADCIRC and GIS. *J. Ocean. Univ. China* **2023**, *22*, 1473–1486. [CrossRef]
104. Castrucci, L.; Tahvildari, N. Modeling the Impacts of Sea Level Rise on Storm Surge Inundation in Flood-Prone Urban Areas of Hampton Roads, Virginia. *Mar. Technol. Soc. J.* **2018**, *52*, 92–105. [CrossRef]
105. Seenath, A.; Wilson, M.; Miller, K. Hydrodynamic versus GIS modelling for coastal flood vulnerability assessment: Which is better for guiding coastal management? *Ocean. Coast. Manag.* **2016**, *120*, 99–109. [CrossRef]
106. Agharroud, K.; Puddu, M.; Ivčević, A.; Satta, A.; Kolker, A.S.; Snoussi, M. Climate risk assessment of the Tangier-Tetouan-Al Hoceima coastal Region (Morocco). *Front. Mar. Sci.* **2023**, *10*, 1176350. [CrossRef]
107. Bruno, M.F.; Motta Zanin, G.; Barbanente, A.; Damiani, L. Understanding the Cognitive Components of Coastal Risk Assessment. *J. Mar. Sci. Eng.* **2021**, *9*, 780. [CrossRef]
108. Hadipour, V.; Vafaie, F.; Kerle, N. An indicator-based approach to assess social vulnerability of coastal areas to sea-level rise and flooding: A case study of Bandar Abbas city, Iran. *Ocean. Coast. Manag.* **2020**, *188*, 105077. [CrossRef]
109. Carneiro-Barros, J.E.; Plomaritis, T.A.; Fazeres-Ferradosa, T.; Rosa-Santos, P.; Taveira-Pinto, F. Coastal Flood Mapping with Two Approaches Based on Observations at Furadouro, Northern Portugal. *Remote Sens.* **2023**, *15*, 5215. [CrossRef]
110. Breilh, J.F.; Chaumillon, E.; Bertin, X.; Gravelle, M. Assessment of static flood modeling techniques: Application to contrasting marshes flooded during Xynthia (western France). *Nat. Hazards Earth Syst. Sci.* **2013**, *13*, 1595–1612. [CrossRef]
111. Fereshtehpour, M.; Karamouz, M. DEM Resolution Effects on Coastal Flood Vulnerability Assessment: Deterministic and Probabilistic Approach. *Water Resour. Res.* **2018**, *54*, 4965–4982. [CrossRef]
112. Kovanen, J.; Oksanen, J.; Sarjakoski, T. Near real-time coastal flood inundation simulation with uncertainty analysis and GPU acceleration in a web environment. *Comput. Geosci.* **2018**, *119*, 39–48. [CrossRef]
113. Makris, C.; Mallios, Z.; Androulidakis, Y.; Krestenitis, Y. CoastFLOOD: A High-Resolution Model for the Simulation of Coastal Inundation Due to Storm Surges. *Hydrology* **2023**, *10*, 103. [CrossRef]
114. Bates, P.; De Roo, A. A simple raster-based model for flood inundation simulation. *J. Hydrol.* **2000**, *236*, 54–77. [CrossRef]
115. Kiesel, J.; Lorenz, M.; König, M.; Gräwe, U.; Vafeidis, A.T. Regional assessment of extreme sea levels and associated coastal flooding along the German Baltic Sea coast. *Nat. Hazards Earth Syst. Sci.* **2023**, *23*, 2961–2985. [CrossRef]

116. Brown, J.M.; Morrissey, K.; Knight, P.; Prime, T.D.; Almeida, L.P.; Masselink, G.; Bird, C.O.; Dodds, D.; Plater, A.J. A coastal vulnerability assessment for planning climate resilient infrastructure. *Ocean. Coast. Manag.* **2018**, *163*, 101–112. [CrossRef]
117. Karamouz, M.; Fereshtehpour, M. Modeling DEM Errors in Coastal Flood Inundation and Damages: A Spatial Nonstationary Approach. *Water Resour. Res.* **2019**, *55*, 6606–6624. [CrossRef]
118. Najafi, M.R.; Zhang, Y.; Martyn, N. A flood risk assessment framework for interdependent infrastructure systems in coastal environments. *Sustain. Cities Soc.* **2021**, *64*, 102516. [CrossRef]
119. Zhang, Y.; Najafi, M.R. Probabilistic Numerical Modeling of Compound Flooding Caused by Tropical Storm Matthew Over a Data-Scarce Coastal Environment. *Water Resour. Res.* **2020**, *56*, e2020WR028565. [CrossRef]
120. Knight, P.J.; Prime, T.; Brown, J.M.; Morrissey, K.; Plater, A.J. Application of flood risk modelling in a web-based geospatial decision support tool for coastal adaptation to climate change. *Nat. Hazards Earth Syst. Sci.* **2015**, *15*, 1457–1471. [CrossRef]
121. Seenath, A. Effects of DEM Resolution on Modeling Coastal Flood Vulnerability. *Mar. Geod.* **2018**, *41*, 581–604. [CrossRef]
122. Skinner, C.J.; Coulthard, T.J.; Parsons, D.R.; Ramirez, J.A.; Mullen, L.; Manson, S. Simulating tidal and storm surge hydraulics with a simple 2D inertia based model, in the Humber Estuary, U.K. *Estuarine, Coast. Shelf Sci.* **2015**, *155*, 126–136. [CrossRef]
123. Zellou, B.; Rahali, H. Assessment of the joint impact of extreme rainfall and storm surge on the risk of flooding in a coastal area. *J. Hydrol.* **2019**, *569*, 647–665. [CrossRef]
124. Coulthard, T.J.; Neal, J.C.; Bates, P.D.; Ramirez, J.; de Almeida, G.A.M.; Hancock, G.R. Integrating the LISFLOOD-FP 2D hydrodynamic model with the CAESAR model: Implications for modelling landscape evolution. *Earth Surf. Process. Landforms* **2013**, *38*, 1897–1906. [CrossRef]
125. Favaretto, C.; Martinelli, L.; Ruol, P. Coastal Flooding Hazard Due to Overflow Using a Level II Method: Application to the Venetian Littoral. *Water* **2019**, *11*, 134. [CrossRef]
126. Zheng, Y.; Sun, H. An Integrated Approach for the Simulation Modeling and Risk Assessment of Coastal Flooding. *Water* **2020**, *12*, 2076. [CrossRef]
127. Jafarzadegan, K.; Muñoz, D.F.; Moftakhari, H.; Gutenson, J.L.; Savant, G.; Moradkhani, H. Real-time coastal flood hazard assessment using DEM-based hydrogeomorphic classifiers. *Nat. Hazards Earth Syst. Sci.* **2022**, *22*, 1419–1435. [CrossRef]
128. Nguyen, T.T.; Bonetti, J.; Rogers, K.; Woodroffe, C.D. Indicator-based assessment of climate-change impacts on coasts: A review of concepts, methodological approaches and vulnerability indices. *Ocean. Coast. Manag.* **2016**, *123*, 18–43. [CrossRef]
129. Gornitz, V. Global coastal hazards from future sea level rise. *Palaeogeogr. Palaeoclimatol. Palaeoecol.* **1991**, *89*, 379–398. [CrossRef]
130. Gornitz, V.M.; Daniels, R.C.; White, T.W.; Birdwell, K.R. The Development of a Coastal Risk Assessment Database: Vulnerability to Sea-Level Rise in the U.S. Southeast. *J. Coast. Res.* **1994**, 327–338. Available online: http://www.jstor.org/stable/25735608 (accessed on 13 February 2025).
131. Jaman, T.; Dharanirajan, K.; Shivaprasad Sharma, S. Assessment of impact of cyclone hazard on social vulnerability of Bhadrak District of Odisha State during Phailin Cyclone in 2013 and Titli Cyclone in 2018 using multi-criteria analysis and geospatial techniques. *Int. J. Disaster Risk Reduct.* **2021**, *53*, 101997. [CrossRef]
132. Hadipour, V.; Vafaie, F.; Deilami, K. Coastal Flooding Risk Assessment Using a GIS-Based Spatial Multi-Criteria Decision Analysis Approach. *Water* **2020**, *12*, 2379. [CrossRef]
133. Silva, S.F.; Martinho, M.; Capitão, R.; Reis, T.; Fortes, C.J.; Ferreira, J.C. An index-based method for coastal-flood risk assessment in low-lying areas (Costa de Caparica, Portugal). *Ocean. Coast. Manag.* **2017**, *144*, 90–104. [CrossRef]
134. Saxena, S.; Geethalakshmi, V.; Lakshmanan, A. Development of habitation vulnerability assessment framework for coastal hazards: Cuddalore coast in Tamil Nadu, India—A case study. *Weather. Clim. Extrem.* **2013**, *2*, 48–57. [CrossRef]
135. Ahmed, M.A.; Sridharan, B.; Saha, N.; Sannasiraj, S.; Kuiry, S.N. Assessment of coastal vulnerability for extreme events. *Int. J. Disaster Risk Reduct.* **2022**, *82*, 103341. [CrossRef]
136. Wang, Y.; Guo, Z.; Zheng, S.; Zhang, M.; Shu, X.; Luo, J.; Qiu, L.; Gao, T. Risk assessment for typhoon-induced storm surges in Wenchang, Hainan Island of China. *Geomat. Nat. Hazards Risk* **2021**, *12*, 880–899. [CrossRef]
137. Zahmatkesh, Z.; Karamouz, M. An uncertainty-based framework to quantifying climate change impacts on coastal flood vulnerability: Case study of New York City. *Environ. Monit. Assess.* **2017**, *189*, 567. [CrossRef]
138. Marín-Monroy, E.A.; Hernández-Trejo, V.; Ojeda-Ruiz de la Peña, M.A.; Romero-Vadillo, E.; Ivanova-Boncheva, A. Perceptions and Consequences of Socioenvironmental Vulnerability Due to Tropical Cyclones in Los Cabos, Mexico. *Sustainability* **2021**, *13*, 6787. [CrossRef]
139. Rocha, C.; Antunes, C.; Catita, C. Coastal Vulnerability Assessment Due to Sea Level Rise: The Case Study of the Atlantic Coast of Mainland Portugal. *Water* **2020**, *12*, 360. [CrossRef]
140. Weis, S.W.M.; Agostini, V.N.; Roth, L.M.; Gilmer, B.; Schill, S.R.; Knowles, J.E.; Blyther, R. Assessing vulnerability: An integrated approach for mapping adaptive capacity, sensitivity, and exposure. *Clim. Chang.* **2016**, *136*, 615–629. [CrossRef]
141. Asbridge, E.F.; Low Choy, D.; Mackey, B.; Serrao-Neumann, S.; Taygfeld, P.; Rogers, K. Coastal flood risk within a peri-urban area: Sussex Inlet district, SE Australia. *Nat. Hazards* **2019**, *109*, 999–1026. [CrossRef] [PubMed]

142. Mullick, M.R.A.; Tanim, A.; Islam, S.M.S. Coastal vulnerability analysis of Bangladesh coast using fuzzy logic based geospatial techniques. *Ocean. Coast. Manag.* **2019**, *174*, 154–169. [CrossRef]
143. Rogers, K.; Woodroffe, C.D. Geomorphology as an indicator of the biophysical vulnerability of estuaries to coastal and flood hazards in a changing climate. *J. Coast. Conserv.* **2016**, *20*, 127–144. [CrossRef]
144. Tahri, M.; Maanan, M.; Maanan, M.; Bouksim, H.; Hakdaoui, M. Using Fuzzy Analytic Hierarchy Process multi-criteria and automatic computation to analyse coastal vulnerability. *Prog. Phys. Geogr. Earth Environ.* **2017**, *41*, 268–285. [CrossRef]
145. Nieto, C.E.; Martínez-Graña, A.M.; Encinas, B. Analysis of the Risk of Coastal Flooding Due to Rising Sea Levels in Ría of Arosa (Pontevedra, Spain). *Appl. Sci.* **2023**, *13*, 2099. [CrossRef]
146. Rohmer, J.; Idier, D.; Paris, F.; Pedreros, R.; Louisor, J. Casting light on forcing and breaching scenarios that lead to marine inundation: Combining numerical simulations with a random-forest classification approach. *Environ. Model. Softw.* **2018**, *104*, 64–80. [CrossRef]
147. Lecacheux, S.; Rohmer, J.; Paris, F.; Pedreros, R.; Quetelard, H.; Bonnardot, F. Toward the probabilistic forecasting of cyclone-induced marine flooding by overtopping at Reunion Island aided by a time-varying random-forest classification approach. *Nat. Hazards* **2021**, *105*, 227–251. [CrossRef]
148. Pachev, B.; Arora, P.; del Castillo-Negrete, C.; Valseth, E.; Dawson, C. A framework for flexible peak storm surge prediction. *Coast. Eng.* **2023**, *186*, 104406. [CrossRef]
149. López-Lopera, A.F.; Idier, D.; Rohmer, J.; Bachoc, F. Multioutput Gaussian processes with functional data: A study on coastal flood hazard assessment. *Reliab. Eng. Syst. Saf.* **2022**, *218*, 108139. [CrossRef]
150. Bass, B.; Bedient, P. Surrogate modeling of joint flood risk across coastal watersheds. *J. Hydrol.* **2018**, *558*, 159–173. [CrossRef]
151. Chondros, M.; Metallinos, A.; Papadimitriou, A.; Memos, C.; Tsoukala, V. A Coastal Flood Early-Warning System Based on Offshore Sea State Forecasts and Artificial Neural Networks. *J. Mar. Sci. Eng.* **2021**, *9*, 1272. [CrossRef]
152. Idier, D.; Aurouet, A.; Bachoc, F.; Baills, A.; Betancourt, J.; Gamboa, F.; Klein, T.; López-Lopera, A.F.; Pedreros, R.; Rohmer, J.; et al. A User-Oriented Local Coastal Flooding Early Warning System Using Metamodelling Techniques. *J. Mar. Sci. Eng.* **2021**, *9*, 1191. [CrossRef]
153. Luo, Z.; Tian, J.; Zeng, J.; Pilla, F. Resilient landscape pattern for reducing coastal flood susceptibility. *Sci. Total. Environ.* **2023**, *856*, 159087. [CrossRef] [PubMed]
154. Ha-Mim, N.M.; Rahman, M.A.; Hossain, M.Z.; Fariha, J.N.; Rahaman, K.R. Employing multi-criteria decision analysis and geospatial techniques to assess flood risks: A study of Barguna district in Bangladesh. *Int. J. Disaster Risk Reduct.* **2022**, *77*, 103081. [CrossRef]
155. Prasad, P.; Loveson, V.J.; Dasc, B.; Kotha, M. Novel ensemble machine learning models in flood susceptibility mapping. *Geocarto Int.* **2022**, *37*, 4571–4593. [CrossRef]
156. Hasan, M.H.; Ahmed, A.; Nafee, K.; Hossen, M.A. Use of machine learning algorithms to assess flood susceptibility in the coastal area of Bangladesh. *Ocean. Coast. Manag.* **2023**, *236*, 106503. [CrossRef]
157. Muñoz, D.F.; Muñoz, P.; Moftakhari, H.; Moradkhani, H. From local to regional compound flood mapping with deep learning and data fusion techniques. *Sci. Total. Environ.* **2021**, *782*, 146927. [CrossRef]
158. Chen, B.; He, J.; He, Z.; Li, L.; Chen, Q.; Li, F.; Chu, D.; Cao, Z.; Xuchao, Y. Potential impacts of storm surge-induced flooding based on refined exposure estimation: A case study in Zhoushan island, China. *Geomat. Nat. Hazards Risk* **2023**, *14*, 2232080. [CrossRef]
159. Mobley, W.; Sebastian, A.; Blessing, R.; Highfield, W.E.; Stearns, L.; Brody, S.D. Quantification of continuous flood hazard using random forest classification and flood insurance claims at large spatial scales: A pilot study in southeast Texas. *Nat. Hazards Earth Syst. Sci.* **2021**, *21*, 807–822. [CrossRef]
160. Anees, M.T.; Abdullah, K.; Nawawi, M.; Ab Rahman, N.N.N.; Piah, A.R.M.; Zakaria, N.A.; Syakir, M.; Mohd Omar, A. Numerical modeling techniques for flood analysis. *J. Afr. Earth Sci.* **2016**, *124*, 478–486. [CrossRef]
161. O'Neill, A.C.; Erikson, L.H.; Barnard, P.L.; Limber, P.W.; Vitousek, S.; Warrick, J.A.; Foxgrover, A.C.; Lovering, J. Projected 21st Century Coastal Flooding in the Southern California Bight. Part 1: Development of the Third Generation CoSMoS Model. *J. Mar. Sci. Eng.* **2018**, *6*, 59. [CrossRef]
162. Androulidakis, Y.; Makris, C.; Mallios, Z.; Pytharoulis, I.; Baltikas, V.; Krestenitis, Y. Storm surges and coastal inundation during extreme events in the Mediterranean Sea: The IANOS Medicane. *Nat. Hazards* **2023**, *117*, 939–978. [CrossRef]
163. Joyce, J.; Chang, N.B.; Harji, R.; Ruppert, T.; Singhofen, P. Cascade impact of hurricane movement, storm tidal surge, sea level rise and precipitation variability on flood assessment in a coastal urban watershed. *Clim. Dyn.* **2018**, *51*, 383–409. [CrossRef]
164. Chen, C.; Beardsley, R.C.; Cowles, G. An Unstructured Grid, Finite-Volume Coastal Ocean Model (FVCOM) System. *Oceanography* **2006**, *19*, 78–89. [CrossRef]
165. Makris, C.; Androulidakis, Y.; Baltikas, V.; Kontos, Y.; Karambas, T.; Krestenitis, Y. HiReSS: Storm surge simulation model for the operational forecasting of sea level elevation and currents in marine areas with harbor works. In Proceedings of the International Scientific Conference DMPCO, Athens, Greece, 8–11 May 2019; Volume 1, pp. 11–15.

166. Silva-Araya, W.F.; Santiago-Collazo, F.L.; Gonzalez-Lopez, J.; Maldonado-Maldonado, J. Dynamic Modeling of Surface Runoff and Storm Surge during Hurricane and Tropical Storm Events. *Hydrology* **2018**, *5*, 13. [CrossRef]
167. Lee, C.; Hwang, S.; Do, K.; Son, S. Increasing flood risk due to river runoff in the estuarine area during a storm landfall. *Estuarine Coast. Shelf Sci.* **2019**, *221*, 104–118. [CrossRef]
168. Dietrich, J.; Zijlema, M.; Westerink, J.; Holthuijsen, L.; Dawson, C.; Luettich, R.; Jensen, R.; Smith, J.; Stelling, G.; Stone, G. Modeling hurricane waves and storm surge using integrally-coupled, scalable computations. *Coast. Eng.* **2011**, *58*, 45–65. [CrossRef]
169. Bush, S.T.; Dresback, K.M.; Szpilka, C.M.; Kolar, R.L. Use of 1D Unsteady HEC-RAS in a Coupled System for Compound Flood Modeling: North Carolina Case Study. *J. Mar. Sci. Eng.* **2022**, *10*, 306. [CrossRef]
170. Moradi, M.; Kazeminezhad, M.H.; Kabiri, K. Integration of Geographic Information System and system dynamics for assessment of the impacts of storm damage on coastal communities—Case study: Chabahar, Iran. *Int. J. Disaster Risk Reduct.* **2020**, *49*, 101665. [CrossRef]
171. Plomaritis, T.A.; Costas, S.; Ferreira, Ó. Use of a Bayesian Network for coastal hazards, impact and disaster risk reduction assessment at a coastal barrier (Ria Formosa, Portugal). *Coast. Eng.* **2018**, *134*, 134–147. [CrossRef]
172. Bolle, A.; das Neves, L.; Smets, S.; Mollaert, J.; Buitrago, S. An impact-oriented Early Warning and Bayesian-based Decision Support System for flood risks in Zeebrugge harbour. *Coast. Eng.* **2018**, *134*, 191–202. [CrossRef]
173. Narayan, S.; Simmonds, D.; Nicholls, R.; Clarke, D. A Bayesian network model for assessments of coastal inundation pathways and probabilities. *J. Flood Risk Manag.* **2018**, *11*, S233–S250. [CrossRef]
174. Coquet, M.; Mercier, D.; Fleury-Bahi, G. Individuals' perceptions of areas exposed to coastal flooding in four French coastal municipalities: The contribution of sketch mapping. *Geoenvironmental Disasters* **2018**, *5*, 15. [CrossRef]
175. Elineau, S.; Longépée, E.; Goeldner-Gianella, L.; Alexandre Nicolae-Lerma, A.; Durand, P.; Anselme, B. Understanding coastal flood risk prevention by combining modelling and sketch maps (Mediterranean coast, France). *Environ. Hazards* **2021**, *20*, 457–476. [CrossRef]
176. Bukvic, A.; Rohat, G.; Apotsos, A.; de Sherbinin, A. A Systematic Review of Coastal Vulnerability Mapping. *Sustainability* **2020**, *12*, 2822. [CrossRef]
177. Chen, Y.H.; Zick, S.E.; Benjamin, A.R. A comprehensive cartographic approach to evacuation map creation for Hurricane Ike in Galveston County, Texas. *Cartogr. Geogr. Inf. Sci.* **2016**, *43*, 68–85. [CrossRef]
178. Muñoz, D.F.; Moftakhari, H.; Moradkhani, H. Compound Effects of Flood Drivers and Wetland Elevation Correction on Coastal Flood Hazard Assessment. *Water Resour. Res.* **2020**, *56*, e2020WR027544. [CrossRef]
179. Al Ruheili, A.; Radke, J. Visualization of 2002 storm surge along the coast of Dhofar, case study of Oman. *Environ. Dev. Sustain.* **2020**, *22*, 501–517. [CrossRef]
180. Olbert, A.I.; Comer, J.; Nash, S.; Hartnett, M. High-resolution multi-scale modelling of coastal flooding due to tides, storm surges and rivers inflows. A Cork City example. *Coast. Eng.* **2017**, *121*, 278–296. [CrossRef]
181. Idier, D.; Rohmer, J.; Pedreros, R.; Le Roy, S.; Betancourt, J.; Bachoc, F.; Lecacheux, S. Coastal Flood at Gâvres (Brittany, France): A Simulated Dataset to Support Risk Management and Metamodels Development. *J. Mar. Sci. Eng.* **2023**, *11*, 1314. [CrossRef]
182. Amante, C.J. Uncertain seas: Probabilistic modeling of future coastal flood zones. *Int. J. Geogr. Inf. Sci.* **2019**, *33*, 2188–2217. [CrossRef]
183. Parry, M.; Canziani, O.F.; Palutikof, J.; van der Linden, P.; Hanson, C.e. *Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007*; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2007.
184. Li, M.; Wu, W.; Wang, J.; Che, Z.; Xie, Y. Simulating and mapping the risk of surge floods in multiple typhoon scenarios: A case study of Yuhuan County, Zhejiang Province, China. *Stoch. Environ. Res. Risk Assess.* **2017**, *31*, 645–659. [CrossRef]
185. Liu, Q.; Ruan, C.; Zhong, S.; Li, J.; Yin, Z.; Lian, X. Risk assessment of storm surge disaster based on numerical models and remote sensing. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *68*, 20–30. [CrossRef]
186. Rey, W.; Martínez-Amador, M.; Salles, P.; Mendoza, E.T.; Trejo-Rangel, M.A.; Franklin, G.L.; Ruiz-Salcines, P.; Appendini, C.M.; Quintero-Ibáñez, J. Assessing Different Flood Risk and Damage Approaches: A Case of Study in Progreso, Yucatan, Mexico. *J. Mar. Sci. Eng.* **2020**, *8*, 137. [CrossRef]
187. Martinelli, L.; Zanuttigh, B.; Corbau, C. Assessment of coastal flooding hazard along the Emilia Romagna littoral, IT. *Coast. Eng.* **2010**, *57*, 1042–1058. [CrossRef]
188. Chen, F.Y.; Yu, P.B.; Wu, X.G.; Zhu, Y.Z. Refined risk assessment of storm surge disaster in coastal plain: A case study of Pingyang county. *J. Trop. Meteorol.* **2019**, *25*, 304–311. [CrossRef]
189. Ghosh, A.; Dey, P. Flood Severity assessment of the coastal tract situated between Muriganga and Saptamukhi estuaries of Sundarban delta of India using Frequency Ratio (FR), Fuzzy Logic (FL), Logistic Regression (LR) and Random Forest (RF) models. *Reg. Stud. Mar. Sci.* **2021**, *42*, 101624. [CrossRef]

190. Sahana, M.; Rehman, S.; Sajjad, H.; Hong, H. Exploring effectiveness of frequency ratio and support vector machine models in storm surge flood susceptibility assessment: A study of Sundarban Biosphere Reserve, India. *CATENA* **2020**, *189*, 104450. [CrossRef]
191. Al-Hinai, H.; Abdalla, R. Mapping Coastal Flood Susceptible Areas Using Shannon's Entropy Model: The Case of Muscat Governorate, Oman. *ISPRS Int. J.-Geo-Inf.* **2021**, *10*, 252. [CrossRef]
192. Wei, M.; Xu, J.; Wang, Y. Resilience Assessment of Traffic Networks in Coastal Cities under Climate Change: A Case Study of One City with Unique Land Use Characteristics. *Land* **2022**, *11*, 1834. [CrossRef]
193. Johnsson, I.; Balstrøm, T. A GIS-based screening method to identify climate change-related threats on road networks: A case study from Sweden. *Clim. Risk Manag.* **2021**, *33*, 100344. [CrossRef]
194. Anarde, K.A.; Kameshwar, S.; Irza, J.N.; Nittrouer, J.A.; Lorenzo-Trueba, J.; Padgett, J.E.; Sebastian, A.; Bedient, P.B. Impacts of Hurricane Storm Surge on Infrastructure Vulnerability for an Evolving Coastal Landscape. *Nat. Hazards Rev.* **2018**, *19*, 04017020. [CrossRef]
195. Huang, W.; Yin, K.; Ghorbanzadeh, M.; Ozguven, E.; Xu, S.; Vijayan, L. Integrating storm surge modeling with traffic data analysis to evaluate the effectiveness of hurricane evacuation. *Front. Struct. Civ. Eng.* **2021**, *15*, 1301–1316. [CrossRef]
196. Ribeiro, A.S.; Lopes, C.L.; Sousa, M.C.; Gomez-Gesteira, M.; Dias, J.M. Flooding Conditions at Aveiro Port (Portugal) within the Framework of Projected Climate Change. *J. Mar. Sci. Eng.* **2021**, *9*, 595. [CrossRef]
197. Yin, Y.; Val, D.V.; Zou, Q.; Yurchenko, D. Resilience of Critical Infrastructure Systems to Floods: A Coupled Probabilistic Network Flow and LISFLOOD-FP Model. *Water* **2022**, *14*, 683. [CrossRef]
198. Synolakis, C.E.; Bernard, E.N. Tsunami science before and beyond Boxing Day 2004. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2006**, *364*, 2231–2265. [CrossRef] [PubMed]
199. Afzal, S.; Hittawe, M.; Ghani, S.; Jamil, T.; Knio, O.; Hadwiger, M.; Hoteit, I. The State of the Art in Visual Analysis Approaches for Ocean and Atmospheric Datasets. *Comput. Graph. Forum* **2019**, *38*, 881–907. [CrossRef]
200. Karamouz, M.; Heydari, Z. Conceptual Design Framework for Coastal Flood Best Management Practices. *J. Water Resour. Plan. Manag.* **2020**, *146*, 04020041. [CrossRef]
201. Khan, M.J.U.; Durand, F.; Emanuel, K.; Krien, Y.; Testut, L.; Islam, A.K.M.S. Storm surge hazard over Bengal delta: A probabilistic–deterministic modelling approach. *Nat. Hazards Earth Syst. Sci.* **2022**, *22*, 2359–2379. [CrossRef]
202. Alarcon, V.J.; Linhoss, A.C.; Kelble, C.R.; Mickle, P.F.; Sanchez-Banda, G.F.; Mardonez-Meza, F.E.; Bishop, J.; Ashby, S.L. Coastal inundation under concurrent mean and extreme sea-level rise in Coral Gables, Florida, USA. *Nat. Hazards* **2022**, *111*, 2922–2962. [CrossRef]
203. Rezaie, A.M.; Haque, A. Development of Storm Surge Inundation Model and Database for Enhanced Climate Services in Bangladesh. *Front. Water* **2022**, *4*, 887631. [CrossRef]
204. Connelly, S.; Vanderhoven, D.; Rutherfoord, R.; Richardson, L.; Matthews, P. Translating research for policy: The importance of equivalence, function, and loyalty. *Humanit. Soc. Sci. Commun.* **2021**, *8*, 191. [CrossRef]
205. Ran, J.; MacGillivray, B.H.; Gong, Y.; Hales, T.C. The application of frameworks for measuring social vulnerability and resilience to geophysical hazards within developing countries: A systematic review and narrative synthesis. *Sci. Total. Environ.* **2020**, *711*, 134486. [CrossRef]

climate

MDPI

Article

Climate Scenarios for Coastal Flood Vulnerability Assessments: A Case Study for the Ligurian Coastal Region

Alice Re [1,*], Lorenzo Minola [1,2,3] and Alessandro Pezzoli [1]

1 Interuniversity Department of Regional and Urban Studies and Planning (DIST), Politecnico di Torino and Università di Torino, 10125 Torino, Italy
2 Regional Climate Group (RCG), Department of Earth Sciences, University of Gothenburg, 41320 Gothenburg, Sweden
3 Climate, Atmosphere and Ocean Laboratory (Climatoc-Lab), Centro de Investigaciones sobre Desertificación, Consejo Superior de Investigaciones Científicas (CIDE, CDIS-UV-Generalitat Valenciana), 46113 Moncada, Valencia, Spain
* Correspondence: alice.re@polito.it

Abstract: Extreme sea levels and coastal flooding are projected to be among the most uncertain and severe consequences of climate change. In response, a wide development of coastal vulnerability assessment methodologies has been observed in research to support societal resilience to future coastal flood risks. This work aims to explore the scope of application of index-based methodologies for coastal vulnerability assessment, in terms of their suitability to convey information on variations in climate variables potentially leading to sea-level changes and inundation. For this purpose, the InVEST Coastal Vulnerability model was coupled for the first time with the ERA5 reanalysis and used to develop a case study assessment of the biophysical exposure component of vulnerability to coastal flooding for Liguria, an Italian coastal region facing the Mediterranean Sea. Different scenarios of wind speed and wave power were created in order to test the sensitivity of this approach to climate data inputs. The results support the applicability of this approach to provide a preliminary grasp of local vulnerability to coastal inundation. Yet, this work also highlights how the method's data aggregation and indicator computation processes result in its insensitivity to wind and wave variations, and therefore in its unsuitability to reproduce climate scenarios. The implications of these findings for research methodology and regarding the operationalisation of vulnerability assessment results are discussed.

Keywords: extreme sea levels; coastal flooding; coastal vulnerability; Mediterranean Sea; ERA5 reanalysis; sea level scenarios

check for updates

Citation: Re, A.; Minola, L.; Pezzoli, A. Climate Scenarios for Coastal Flood Vulnerability Assessments: A Case Study for the Ligurian Coastal Region. *Climate* **2023**, *11*, 56. https://doi.org/10.3390/cli11030056

Academic Editors: Charalampos Skoulikaris and Christina Anagnostopoulou

Received: 24 January 2023
Revised: 23 February 2023
Accepted: 27 February 2023
Published: 1 March 2023

1. Introduction

Assessing the vulnerability of coastal communities to climate-related hazards is a key aspect of climate change adaptation [1,2]. Coastal flooding has been recognised in scientific literature as the most relevant among the many potential hazards related to climate change for coastal communities, due to its frequency and damage potential [3]. Because of the combination of the regional orography and its latitude range resulting in a concentration of all the main natural risks linked to the water cycle [4], the Mediterranean Sea basin is considered to be one of the most vulnerable areas to climate change impacts [5,6]. The quasi-homogeneous signal of Global Mean Sea Level (GMSL) rise, combined with changes in the northeast Atlantic circulation are likely to lead to the average sea level in the Mediterranean Sea rising between 40 and 100 cm at the end of the 21st century, with respect to current values [4]. There is a lack of consensus in scientific literature regarding future projections of Extreme Sea Levels (ESLs); these have been demonstrated to be highly sensitive to the choice of atmospheric forcing, and model simulation results have shown marked differences and low spatial coherence [4]. It is nevertheless widely accepted that, worldwide, today's 100-year event will become common by the end of the century under all Representative Concentration Pathway (RCP) scenarios [1]. Some notable literature contributions regarding ESLs in the Mediterranean Sea point instead towards a reduction in the average number [7] and magnitude [8] of positive surges, as well as lower values of extreme wind waves [9].

As with other climate change-related risks, flood risk is determined by the interaction of biophysical and social factors [10]. Climate drivers vary in time resulting from the interaction of natural variability and anthropogenic climate change, and contextual characteristics play a role in determining how the flood event will unfold in and impact the specific context [11,12]. Assuming current levels of coastal protection standards to remain unchanged in the future, absolute coastal flood risk is projected to increase strongly because of a combination of climate-induced ESL changes and socioeconomic drivers [13]. Coastal areas are generally associated to a large number of social and economic activities concentrated near the shoreline [2,14] and assets exposed to such extreme events are expected to increase dramatically in the upcoming decades [15,16]. In the EU, one third of the population already lives within 50 km of the coast, and by the end of this century 5 million EU citizens could be annually at risk from coastal flooding [17].

Given the relevance and perceived urgency of the topic, a widespread uptake of coastal vulnerability appraisals has been observed both in research and practice. A variety of frameworks (e.g., the 1991 IPCC Common Methodology [10]), assessment methodologies and indices has been proposed within the field, mirroring the context and purpose-dependency of the concept [2,3] and the breadth of the field of vulnerability to climate change at large. Methodologies including numerical flood modelling (e.g., [18]), the vulnerability curve method, the disaster loss data method [19], indicator-based methodologies (of which [2] and [20] have provided comprehensive reviews) and Multi Criteria Decision Analysis (MCDA) (e.g., [21]) have been used in order to assess coastal flood vulnerability, depending on the research objectives and on the resources available [3]. Among the most widely accepted methodologies for flood vulnerability assessment, indicator-based methodologies have met with particular success because of their overall ability to convey relatively comprehensive information in a quick and not overly computationally-intensive manner [12].

The Coastal Vulnerability Index (CVI) [22,23] represents possibly the earliest attempt at providing an indicator-based assessment methodology of vulnerability to coastal flooding and erosion, with a main focus on the physically-based drivers of vulnerability. Other methodologies were then proposed to also account for the socioeconomic components of coastal vulnerability, such as the Coastal Social Vulnerability Index (CSoVI) [24,25].

Specific approaches have also been devised in order to depict the complex interactions among catchment hydrology and coastal processes in low-lying deltaic environments, such as the Coastal Cities Flood Vulnerability Index (CCFVI) [26] and the Integrated Deltaic Risk Index (IDRI) [27]. The latter is a hybrid approach which utilises numerical model results on different locally-relevant climate and hydrological processes as an input for computing an aggregate risk index.

The most relevant shortcomings within the field of flood vulnerability assessment regard for the most part a generalised lack of standardisation in practices, methodologies [2] and terminology [12], hindering the propagation of good practices and the comparability of research outcomes. The paucity of sensitivity, uncertainty [3,28] and validation analyses provided as complementary to vulnerability assessment results [29] has also been shown to impair their validity in terms of a cognizant and proper incorporation of research outcomes in policy processes. When it comes to indicator-based assessment methodologies, these exhibit critical issues also with regards to the data choice, aggregation and weighting processes leading to a final aggregate indicator [2,30], and regarding the transparency of underlying assumptions not being conveyed by some types of indicators [31].

Within this context, this work aims at addressing some of the relevant shortcomings presented above through a case study assessment of the physical exposure component of vulnerability to coastal flooding, particularly with regards to the study of indicator sensitivity to different climate scenarios. Namely, the focus is to better outline the scope of application of indicator-based methodologies in terms of their suitability to accurately convey information on the underlying variations in climate variables, and to consequently be appropriate tools to depict climate scenarios fit to inform policy action. For this reason, attention was directed towards the characterisation and inclusion within the analysis of relevant climate variables determining extreme sea levels and storm conditions in coastal areas. In order to do so, the consequences of data aggregation and indicator computation processes were investigated through sensitivity and validation analyses for data on wind speed and wave power.

Liguria, an Italian coastal region facing the Mediterranean Sea, was chosen as area of interest for the analysis. Because of a combination of geomorphological characteristics (e.g., high slopes contributing to high runoff speeds for pluvial floods [32]), presence of densely populated urban areas, high soil sealing rates and local climate, this region has historically faced dire consequences related to pluvial and coastal flood events [33]. The case study assessment was carried out using the InVEST Coastal Vulnerability model [34,35], a well established methodology which provides an index-based assessment of vulnerability to coastal floods and coastal erosion in a spatially-explicit manner.

The contribution of this work to the field of research on coastal vulnerability assessments is threefold. The first contribution regards the broad methodological issue of the study of model and indicator sensitivity to climate change scenarios mentioned above in this section, which represents the main research gap this work aims to address. Secondly, this work originally contributes to research in terms of the geographical context of choice: to the best of the authors' knowledge, most of the published peer-reviewed articles which utilised the InVEST Coastal Vulnerability model focused on oceanic coasts, and none provided examples of its application to coastal areas in the Mediterranean Sea. This article attempts a first application of this methodology to this semi-enclosed sea basin, which entailed tuning model parameters with regards to the limited fetch conditions as well as to the local geomorhphology and coastal habitats. Finally, this case study also represents a first example of coupling the ERA5 reanalysis dataset [36] with this specific coastal vulnerability assessment model, in order to produce scenarios of past climate conditions influencing sea levels locally. Utilising the ERA5 dataset in place of the default Wavewatch III data suggested for use within this InVEST model [35] is particularly relevant in view of the need to account for the context-dependency of climate change impacts by tailoring the methodology of choice to regional characteristics.

Quagliolo et al. [32] proposed an assessment of pluvial flash floods with a focus on Nature-Based Solutions (NBS) for urban flood risk mitigation, for a series of watersheds within the Metropolitan area of Genoa, Liguria. As compound and multi-pathway flooding is at the forefront of research in coastal areas [37], the work presented here further complements the aforementioned analyses by assessing exposure to coastal floods for roughly the same geographical area. Such analyses help highlighting the multitude of potential flooding pathways in the region, also in support of future economic appraisals of climate change impacts and climate adaptation policies for urban coastal environments.

The continuation of this work is articulated as follows: Section 2 presents the study area and the data inputs, and addresses how the latter were used within the InVEST Coastal Vulnerability model. Notably, this section highlights the data on relevant climate variables included in the analysis and the creation of climate scenarios to input in different model runs. Section 3 addresses the analysis results; a general overview of the model outputs is introduced, together with an analysis of the model's sensitivity to changes in climate data inputs and an attempt at results validation. Section 4 poses a critical discussion of the scope of application of the methodology of choice by addressing its potential and limitations, especially with regards to its use to represent different ESL scenarios in coastal areas. Future research developments in light of the case study results and discussion are additionally examined therein. Conclusions are drawn in Section 5.

2. Materials and Methods

2.1. Study Area

A sizable portion of coastline in the Italian region Liguria—corresponding roughly to the Gulf of Genoa and spanning approximately 440 km—was chosen as the area of interest for the case study presented in this article (see Figure 1). The region's orography and densely forested surface have caused most of the population and urbanised areas to concentrate in close proximity to the coastlines [32]; the Metropolitan area of Genoa alone houses more than half the regional population (816,250 people out of the regional total of 1,507,438) [38].

Low-lying coasts are located predominantly in the western side of the region, while cliffs and high coasts are more prevalent in the eastern side of the Region, from the Portofino promontory and further towards the Toscana region. Estuaries and river mouths of modest size can be found throughout the regional coastlines. Some major urban areas including those of the Genoa and La Spezia municipalities are located at particularly low elevations above the sea level and/or in close proximity to river mouths.

Liguria is characterised by a Mediterranean climate; data on cumulative monthly precipitation collected at a weather station in Genoa (*Genova Università* weather station, located at 58 m MSL) for the period 1981–2010 averaged maximum values of just above 210 mm, with September to November being the rainiest months of the year [39].

According to regional projections from the National Climate Change Adaptation Plan [40], the mean sea level in the Ligurian sea's coastal areas (i.e., within 12 nautical miles from the coastline) [41] might increase by 8 cm in the period 2021–2050 under the RCP8.5 scenario.

Data on relevant oceanographic variables are collected by a measurement buoy located in proximity to La Spezia, on the Eastern side of Liguria [42]. According to both observations from the buoy and to modelled hindcasts, most of the coastal storms come from the Libeccio direction (S-SW). In the area, wave heights of 7.4 m on average are associated to a return period of 100 years (average of relevant modelled locations close to La Spezia) [43].

In the recent past, some extreme events leading to flooding have occurred over the study area, both in terms of pluvial flash floods caused by extreme rainfall [32] and in terms of coastal storms causing extreme sea levels [44]. One such extreme coastal storm is referenced later in Section 2.6, and was used as a worst-case scenario event to set some of the model's parameters for the case study development.

2.2. The InVEST Coastal Vulnerability Model

The InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) [34] Coastal Vulnerability model was used for this case study (version 3.10.1). This methodology was chosen for the development of this work because it represents a well-established example of indicator-based assessment methodology for coastal vulnerability assessment. This model aims to provide spatially-explicit, modular and scenario-driven analyses to inform spatial planning in the coastal zone [45], with a particular focus on the role of coastal habitats to provide protection from erosion and inundation. There are extensive examples in literature utilising the InVEST Coastal Vulnerability model to address the topics of vulnerability and Nature-Based Solutions (NBS), green infrastructure and coastal planning (e.g., [45–50]). Though, the application of this methodology to a coastal area in the Mediterranean Sea and the in-depth study of the methodology and implications of accounting for climate scenarios within this approach represent—to the best of the author's knowledge at the time of writing—original research contributions of this work.

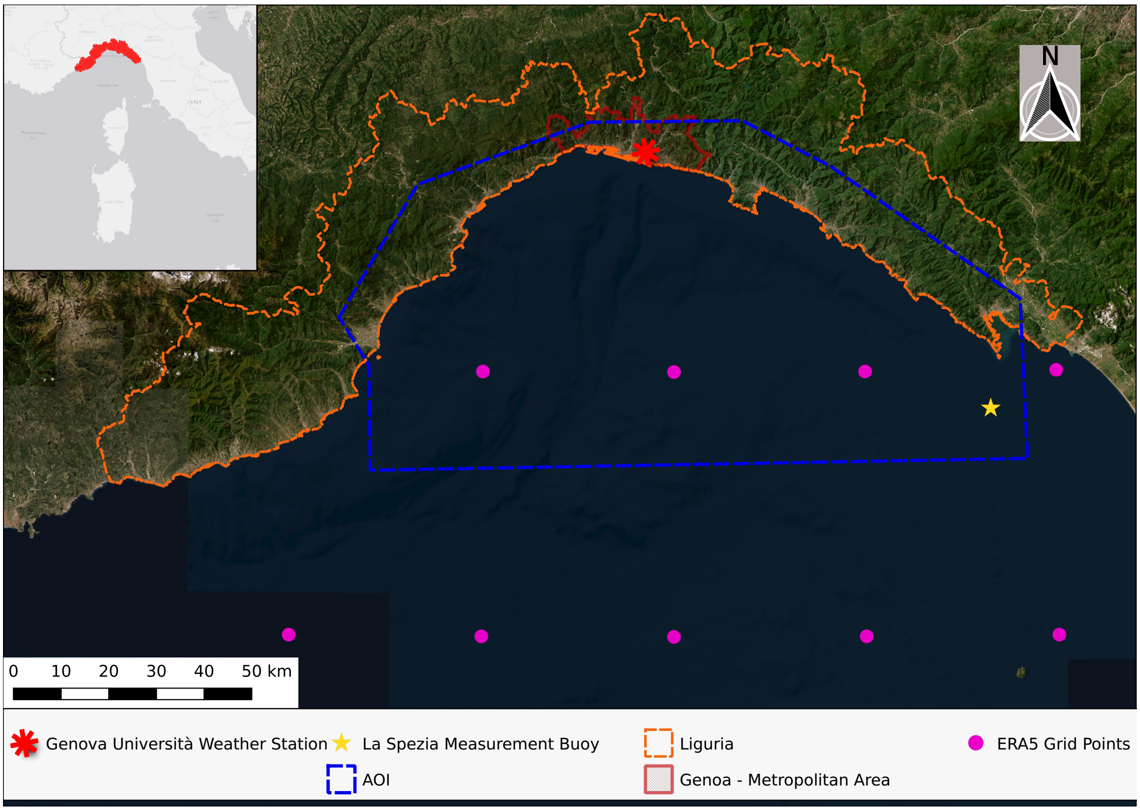

Figure 1. Map of the study area. The La Spezia measurement buoy and the *Genova Università* weather station referenced in Section 2.1 are represented respectively as a yellow star and as a red asterisk. The Area of Interest (AOI) within which the InVEST Coastal Vulnerability model was run is marked by the blue dotted line. The location of the ERA5 grid points used for retrieval of climate data are represented as pink dots.

The InVEST Coastal Vulnerability model outputs an Exposure Index (EI) and several sub-indices of exposure for each of a series of evenly-spaced shore points along the coastline within a user-defined Area of Interest (AOI). The model computes the EI as the geometric mean of a series of sub-indices about relevant bio-geophysical variables contributing to exposure to coastal hazards in the area: wind exposure, wave exposure, sea level change (optional input, not included in this case study), relief, surge potential, geomorphology (optional input), natural habitats. Both the sub-indices and the overall EI range between ranks 1 to 5, corresponding respectively to very low exposure and very high exposure. The choice, aggregation and ranking of variables adopted by the model build upon the Coastal Vulnerability Index (CVI) proposed by [22,23]. Section 2.7.2 details the data aggregation and indicator computations carried out by the model in more detail.

The shore points are spaced at a user-defined model resolution, which varies depending on the case study at hand and can be adjusted to account for input data resolution, intended use of the model output and processing time. A model resolution of 1000 m was chosen for this case study.

The following sections present a description of the data used to develop this case study, subdivided into three main categories: data on terrain features, data on climate variables influencing storm conditions and sea levels in the coastal area, data on coastal habitats. A summary of the data inputs is provided in Table 1, including their sources and the corresponding bio-geophysical variable within the InVEST Coastal Vulnerability model.

2.3. Data on Terrain Features

2.3.1. Digital Elevation Model

A Digital Elevation Model (DEM) is required by the model in order for it to compute the *relief* sub-index for each shore point, under the general assumption that on average locations at higher elevation above the sea level are less exposed to inundation. DEMs are at the core of most flood modelling efforts—not just for coastal applications—as they provide a general description of the hydraulic connectivity of the terrain upon which water flows, even if in a very approximate manner [18]. A significant number of coastal risk applications rely on publicly available DEMs in order to delineate flood extents [3]: their availability at high resolution has been recognised as a crucial factor to achieve good results in terms of modelled flood extent and consequences [18]. The DEM (raster dataset with a 5 m $\times$ 5 m pixel resolution, 2022 edition) for Liguria was retrieved from *Geoportale Liguria*.

2.3.2. Geomorphology

The ability of the shoreline to provide protection from inundation and erosion is calculated by the model based on the average elevation above sea level of a given shoreline portion. Though, low-lying stretches of the coast might be reinforced by means of artificial shore-parallel structures to achieve extra protection in otherwise very exposed areas. Such information can optionally be included in the analysis by providing the *geomorphology* data input to the model. The geomorphology input was created in the form of a polyline shapefile vector representing the different shoreline segments within the AOI based on information provided within the *Sistema Informativo della Costa (SICOAST)* framework. All relevant vector datasets containing information on the geomorphological characteristics of the coast (see Table 1) were processed in order to capture the variety of the different shoreline types within the AOI according to model specifications. The final ranks assigned to the geomorphology layer (see Section 2.7.2), as well as the different shoreline types considered, are listed in Appendix A.

2.3.3. Bathymetry and Continental Shelf Edge Location

Bathymetry data were originally collected to ensure navigation safety, but have later found widespread use across several other fields, including ocean currents modelling [51]. The InVEST Coastal Vulnerability model requires information on seafloor topography for the study region in two different ways.

Digital Bathymetry Models (DBMs) are digital terrain models that represent the topography of the sea floor, typically in the form of regular grids with depth values assigned to individual grid cells. A DBM raster dataset is used by the model to extract values of water depth in order to perform calculations of wave period and height for the local wave exposure [35]. The *European Marine Observation and Data Network* (EMODnet) bathymetry grid was used for this case study.

The second seafloor-related information is the location of the edge of the continental shelf, or other user-specified and more locally relevant bathymetry contours, in order to compute the *surge* sub-index. Among other factors, storm surge elevation is a function of the amount of time wind blows over relatively shallow waters. Therefore, the longer the distance between the coastline and the edge of the continental shelf, the higher the exposure to storm surge which will be calculated by the model. The default global dataset on the location of the continental shelf edge provided by the InVEST model developers was used to run the model.

2.4. Climate Data Inputs—Reanalysis Product Description

Data on relevant climate variables contributing to coastal flood hazard in the area were obtained from the ERA5 reanalysis [36]. ERA5 provides a detailed record of the global atmosphere, land surface and ocean waves from 1950 onwards at a 0.25° $\times$ 0.25° horizontal resolution for the atmosphere and 0.5° $\times$ 0.5° for ocean waves [52]. Reanalysis datasets are spatially complete and physically coherent simulations of climate processes and variables.

They are obtained by a process of data assimilation in which observational data are fed into a forecast model [53]. Because of these features, these datasets are particularly important for the study of climate change trends and consequences, as they allow to overcome hindrances related to data fragmentation.

ERA5-derived data on climate variables relevant to the development of flood events has previously been used to study climate change impacts in the Mediterranean Sea and over the Italian territory [54]. When it comes to the description of sea-level changes, previous literature highlighted how ERA5's horizontal resolution might lead to poor results in particularly narrow regional seas [55]. Dynamical downscaling of ERA5-derived data has been shown to improve hindcast reliability in coastal areas, especially when it comes to wind and wave directions when compared to the original low-resolution dataset [56]. Nevertheless, ERA5 has shown a good performance reproducing observed seasonal cycles of wind speed and wind gusts in coastal areas dominated by regional and local circulations [53]. Therefore, ERA5 still represents the best long-term reanalysis product to study wave climatology in the Mediterranean Sea [55], and was considered as a suitable choice for use in this case study assessment given the geographical and time resolutions of the analysis.

Nine ERA5 grid points located off the Ligurian coast (see Figure 1) were selected for data retrieval. Notably, the near-surface (10 m height) wind speed (m/s) was obtained following specifications provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) [57] starting from the ERA5 u-component of 10-m wind (u10) and the ERA5 v-component of 10-m wind (v10).

The second climate-related variable for use in the model is the wave energy flux per unit of wave-crest length (W/m). It was calculated following specification by [58,59] starting from the ERA5 significant height of combined wind waves and swell, the ERA5 peak wave period and the ERA5 mean wave direction.

Sea level change is an optional climate-related input for the Coastal Vulnerability model. It was not accounted for in this case study, as the AOI was assumed to be sufficiently limited that there should not be any variability in the rate or amount of sea level change within it [1,60].

30-Year Climate Periods

There is scientific consensus that 30-year periods are recommended for calculation of the climate normal, since such a time span is supposed to be long enough to be able to express relatively representative and stable climatic patterns [61]. One of the objectives of this case study was to test the suitability of the model of choice to account for variations in climate patterns and develop climate scenarios. The focus of the study was not placed on testing the use of longer climate periods as input for the analysis, but rather on comparing the model outputs based on different representative climate periods. In order to do so, wind and waves model inputs were split into two different 30-year periods, one spanning 1961 to 1990 [62] and the other spanning 1991 to 2020. The two subsets were used as input for two different runs of the model in order to compare variations in its outputs, keeping all other inputs equal. By doing so, the intention was to eventually be able to identify changes in the model outcomes—and thus changes in vulnerability—brought about exclusively by changes in climate.

2.5. Data on Coastal Habitats

Nature-Based Solutions (NBS) can be understood as "solutions to societal challenges that involve working with nature [...]", simultaneously addressing the challenges of "[...] mitigating and adapting to climate change, protecting biodiversity and ensuring human wellbeing [...]" [63]. The role of natural habitats as NBS and green infrastructure as means to provide benefits to society and protect it from adverse situations has received widespread attention in research and policy with regards to both adaptation and mitigation of climate change [64,65]. Natural habitats show dynamic and non-linear responses to climate change-related processes and can't be assumed to be passive elements of the landscape [6]; because of the complexity of the processes at hand, the quantification of the potential to reduce the impacts of climate change of NBS has shown to be a challenging task [32].

With regards to coastal environments, though most of the analyses of coastal vulnerability to the effects of climate change still seems to focus on hardening shorelines, coastal ecosystem have been estimated to be able to reduce by approximately 50% the proportion of people and property most exposed to sea-level rise and coastal storms in some areas [66]. The potential of seaweeds and seagrass meadows to attenuate waves and intercept and stabilise sediment thus reducing erosion of sandy beaches in several different environments is well documented in literature (e.g., [67–69]). Coral reefs are also of particular interest because of their ability to act as natural breakwaters capable of effectively dissipating wave energy [68].

The InVEST Coastal Vulnerability model aims to identify shoreline portions where habitats are most likely to reduce coastal hazards such as inundation and erosion. Geospatial information on habitat distribution off the Ligurian coast was retrieved from the *Atlante degli Habitat Marini della Liguria* in the form of a polygon vector shapefile highlighting the location of the different coastal habitats in the AOI (see Table 1). The habitats considered in this case study are three types of seaweed/algae (*caulerpa*, *sciaphilous* and *photophilic* algae), two types of seagrass (*posidonia oceanica* and *cymodocea nodosa*) and the coralligenous biocoenosis, a Mediterranean Sea formation analogous to coral reefs [70]. The protection ranks assigned to the habitat data input (see Section 2.7.2) are listed in Appendix A.

Table 1. Data inputs for the InVEST Coastal Vulnerability model runs.

Data Layer Name	Data Type and Spatial Resolution	Source	Reference Year(s)	Bio-Geophysical Variable
Digital Elevation Model (DEM)	Raster; 5 m × 5 m	https://geoportal.regione.liguria.it/catalogo/mappe.html Geoportale Liguria (accessed on 6 June 2022)	2022	Relief
Linea di Costa	Vector; 1:5000	https://geoportal.regione.liguria.it/catalogo/mappe.html Geoportale Liguria (accessed on 22 February 2022)	2019	Geomorphology
Spiagge	Vector; 1:5000	https://geoportal.regione.liguria.it/catalogo/mappe.html Geoportale Liguria (accessed on 22 February 2022)	2016	Geomorphology
Costa Alta	Vector; 1:5000	https://geoportal.regione.liguria.it/catalogo/mappe.html Geoportale Liguria (accessed on 22 February 2022)	2016	Geomorphology

Table 1. *Cont.*

Data Layer Name	Data Type and Spatial Resolution	Source	Reference Year(s)	Bio-Geophysical Variable
Opere di Difesa Costiere	Vector; 1:5000	https://geoportal.regione.liguria.it/catalogo/mappe.html Geoportale Liguria (accessed on 22 February 2022)	2016	Geomorphology
EMODnet Bathymetry	Raster; 1/16 arc minute	https://portal.emodnet-bathymetry.eu/# EMODnet Product Catalogue (accessed on 30 May 2022)	2018	Wave Height and Period
Continental Shelf Edge	Vector; NA	http://releases.naturalcapitalproject.org/?prefix=invest/3.11.0/data/ Default Datasets NatCap Project (accessed on 6 January 2022)	NA	Surge
ERA5 u-component of 10-m wind (hourly data)	Raster; 0.5° × 0.5°	https://cds.climate.copernicus.eu/#!/home CDS Website (accessed on 2 March 2022)	1961–1990; 1991–2020	Wind Speed
ERA5 v-component of 10-m wind (hourly data)	Raster; 0.5° × 0.5°	https://cds.climate.copernicus.eu/#!/home CDS Website (accessed on 2 March 2022)	1961–1990; 1991–2020	Wind Speed
ERA5 significant height of combined wind waves and swell (hourly data)	Raster; 0.5° × 0.5°	https://cds.climate.copernicus.eu/#!/home CDS Website (accessed on 2 March 2022)	1961–1990; 1991–2020	Wave Power
ERA5 peak wave period (hourly data)	Raster; 0.5° × 0.5°	https://cds.climate.copernicus.eu/#!/home CDS Website (accessed on 2 March 2022)	1961–1990; 1991–2020	Wave Power
ERA5 mean wave direction (hourly data)	Raster; 0.5° × 0.5°	https://cds.climate.copernicus.eu/#!/home CDS Website (accessed on 2 March 2022)	1961–1990; 1991–2020	Wave Power
Atlante Habitat Marini della Liguria	Vector; 1:10,000	https://geoportal.regione.liguria.it/catalogo/mappe.html Geoportale Liguria (accessed on 28 November 2022)	2020	Habitats

2.6. Model Parameters

User-defined parameters are required to set the *maximum fetch distance* and the *elevation averaging radius*. The former is needed to discern between ocean-driven waves and locally-generated wind-driven waves. The latter is the radius within which the model computes average elevation from the DEM in order to estimate the *relief* sub-index.

For this case study, the two parameters were set based on projects of port infrastructure for the Port of Genoa [71] as well as on data pertaining to the storm surge episode of late October 2018, considered as a worst-case scenario situation. Beginning in the late evening of 29 October 2018, an exceptional weather event affected a wide portion of Liguria. A combination of heavy rainfall in the previous days and storm conditions (waves up to 10 m high registered in Capo Mele and wind gusts of up to 180 km/h registered at Marina di Loano [44]) resulted in a storm surge causing heavy damage to the coastline, particularly in Santa Margherita Ligure and Rapallo.

400 km was set as the maximum fetch distance parameter, while the elevation averaging radius was set at 100 m, corresponding to the maximum registered inundation extent inland during the 2018 storm event.

2.7. Methodology

The methodology adopted for the development of the case study assessment described in this article is illustrated in Figure 2.

2.7.1. Data Retrieval, Pre-Processing and Scenario Creation

After data retrieval from various sources, data pre-processing was carried out in a GIS environment for the geomorphology and habitat data inputs in order for them to fit to model specifications. Protection ranks for these two inputs were assigned according to model guidelines [35] (see Section 2.7.2 and Appendix A). With regards to the DBM, a quality comparison following specifications from [51] was carried out between the default global dataset recommended by model developers (*General Bathymetric Chart of the Oceans*, GEBCO [72]) and the EMODnet bathymetry. EMODnet data was ultimately selected as it provided superior quality within the AOI. Two 30-year climate scenarios were created for model output comparison as described above.

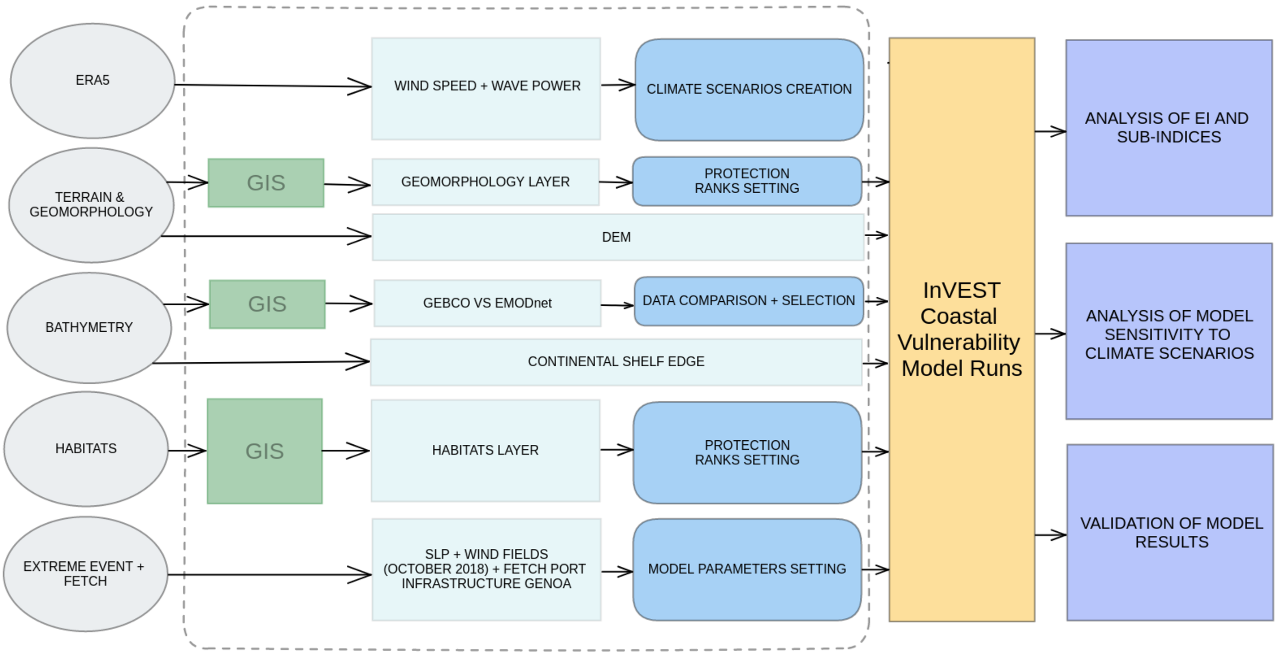

Figure 2. Case study workflow. Grey ellipses represent the main categories of data sources. Data for which a pre-processing has been carried out in a GIS environment (geomorphology and habitat data for data selection and shapefile creation, bathymetry data for quality comparison within the AOI) are connected to the corresponding green rectangles. The main data pre-processing, data selection, parameters setting and scenario creation steps are summarised in the middle part of the workflow (delineated by a dotted perimeter). The three main data analysis steps carried out on model results are pictured as dark blue rectangles on the right of the workflow diagram.

2.7.2. Data Processing by the Model

The InVEST Coastal Vulnerability model output is provided as a series of georeferenced shore points. Each shore point is associated to: (i) an overall Exposure Index (EI), (ii) one sub-index for each bio-geophysical variable of interest, and (iii) a series of intermediate outputs that work as the sub-indices' precursors.

The model computes intermediate outputs differently for each bio-geophysical variable considered (see Table 2). For the wind exposure, wave exposure, surge potential and relief sub-indices, these are computed pointwise directly by the model, starting from input data and model parameters. Intermediate outputs then get arranged in an ordered distribution and assigned to 5 bins of 20% of the distribution each, coincident with ranks 1 to 5. The shore point's rank represents its value respective to the corresponding sub-index.

The geomorphology and habitat sub-indices are instead calculated by the model starting from ranks assigned to input data by the model user. Specifically, geomorphology ranks are assigned by the user to individual segments of a shoreline polyline vector shapefile provided as geomorhpology input to the InVEST model. The model then computes the final geomorphology sub-index pointwise, as the average rank of shoreline segments found within a given radius (i.e., half the model resolution) around each shore point [35]. Habitat ranks are assigned by the user to individual polygons of a vector shapefile provided as habitat input to the InVEST model. The model then computes the final habitat sub-index pointwise based on the ranks of habitats found within a given radius (i.e., the habitat protection distance, see Table A2) around each shore point [35].

Lastly, the model computes the EI for each shore point as:

$$EI = \left(\prod_{i=1}^{n} R_i\right)^{1/n} \tag{1}$$

where R_i stands for each sub-index computed by the model.

Table 2. Adaptation of the guidance ranking table for the InVEST Coastal Vulnerability model proposed by [35] [perc. = percentile]. The last column highlights the rank calculation method for each sub-index considered in the case study, differentiating between ranks computed by the model for each shore point based on intermediate outputs and ranks assigned by the model user to the different geomorphological or habitat categories present in the respective data inputs. Ranks assigned to geomorphology and habitat data inputs in this case study are reported in Tables A1 and A2.

Model Sub-Index	**Rank**					**Rank Calculation Method**
	1 (lowest)	**2** (low)	**3** (intermediate)	**4** (high)	**5** (highest)	
Wind Exposure	0–20 perc.	21–40 perc.	41–60 perc.	61–80 perc.	81–100 perc.	Computed by the model
Wave Exposure	0–20 perc.	21–40 perc.	41–60 perc.	61–80 perc.	81–100 perc.	Computed by the model
Surge Potential	0–20 perc.	21–40 perc.	41–60 perc.	61–80 perc.	81–100 perc.	Computed by the model
Relief	81–100 perc.	61–80 perc.	41–60 perc.	21–40 perc.	0–20 perc.	Computed by the model
Geomorphology	e.g., rocky high cliffs	e.g., indented coasts	e.g., low cliffs	e.g., cobble beach	e.g., sand beach	Assigned by user
Natural Habitats	e.g., coral reef	e.g., marsh	e.g., low dunes	e.g., sea grass	e.g., no habitats	Assigned by user

3. Results

Running the InVEST Coastal Vulnerability model at a resolution of 1000 m within the AOI generated 457 shore points. Figures 3 and 4 show the model output in a GIS environment: each shore point is coloured based on the values of the overall EI. The EI distribution has been subdivided in 5 equal quantiles corresponding to 20% of the distribution each for the purpose of styling, to which qualitative labels of 'lowest' to 'highest' have been assigned within the map. Figure 5 presents the distribution of the EI for the current climate period and highlights its subdivision in quantiles mentioned above.

Table 3 shows summary statistics of the EI and the *habitat* and *geomorphology* sub-indices. No summary statistics are provided for the *wind*, *wave*, *surge* and *relief* sub-indices because they are computed in such a way that there is always going to be the same amount of shore points for each of the ranks spanning 1 to 5 (integers only).

3.1. General Overview of the Outputs

In general, shoreline stretches ranking worse with respect to the overall AOI in terms of the EI are located mostly in front of the port areas of Genoa and La Spezia, to the east of the Portofino promontory (Chiavari and Lavagna municipalities) and close to the westernmost portion of the AOI, in the Savona province (Albenga and Loano municipalities). Some portions of the shoreline present a particularly complex morphology, particularly in port areas where the landmass vector used as input to the model accurately depicts port and coastal defense infrastructure. This is particularly true for the Genoa and La Spezia port areas. Zooming over those areas as shown in Figure 4 allows to highlight that in those complex port areas the model identifies how some portions such as breakwaters are at highest exposure, whereas the innermost portions of portal areas are ranked as less exposed.

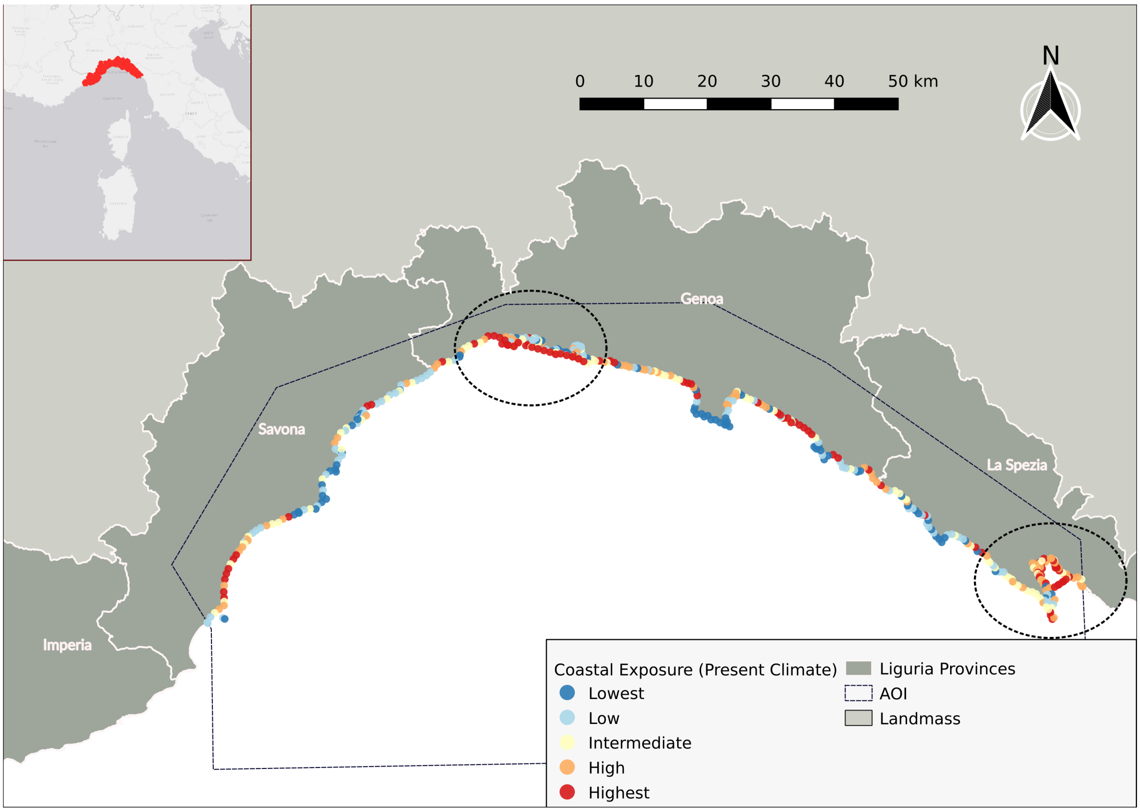

Figure 3. Map of the Exposure Index for the whole area considered in the case study assessment. The Area of Interest (AOI) polygon within which the InVEST Coastal Vulnerability model was run is also highlighted in the map. Liguria's location within the rest of the landmass is highlighted in red in the upper left corner of the map. Dotted ellipses delineate the location of the two main port areas of the AOI, for which zoomed maps are proposed in Figure 4.

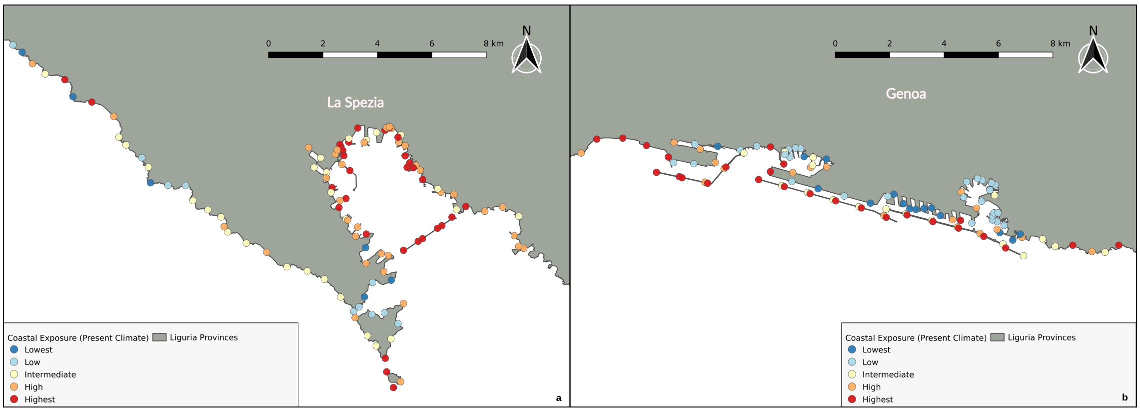

Figure 4. Map of the Exposure Index. Image zooms on the port areas of (**a**) La Spezia and (**b**) Genoa highlighting the location of the shore points on portal infrastructure. The location of the two areas within the broader regional context is highlighted in Figure 3. The shore points are styled in the same way as in the map of the whole area considered.

Each shore point is associated to values of both the overall EI and individual sub-indices of each bio-geophysical variable contributing to physical exposure. Because of the EI construction (see Section 2.7.2), it is possible for two contiguous shore points to have very different EI values, as it can be noticed in Figure 4. In particular, this happens frequently for shore points that have the same wind and wave exposure, but that fall on shoreline segments that have very different relief or geomorphology ranks: keeping the climate exposure fixed, the shore points located higher above water or in proximity to shoreline defense infrastructure will be less exposed in terms of the relief and geomorphology sub-indices and eventually rank differently in terms of the overall EI.

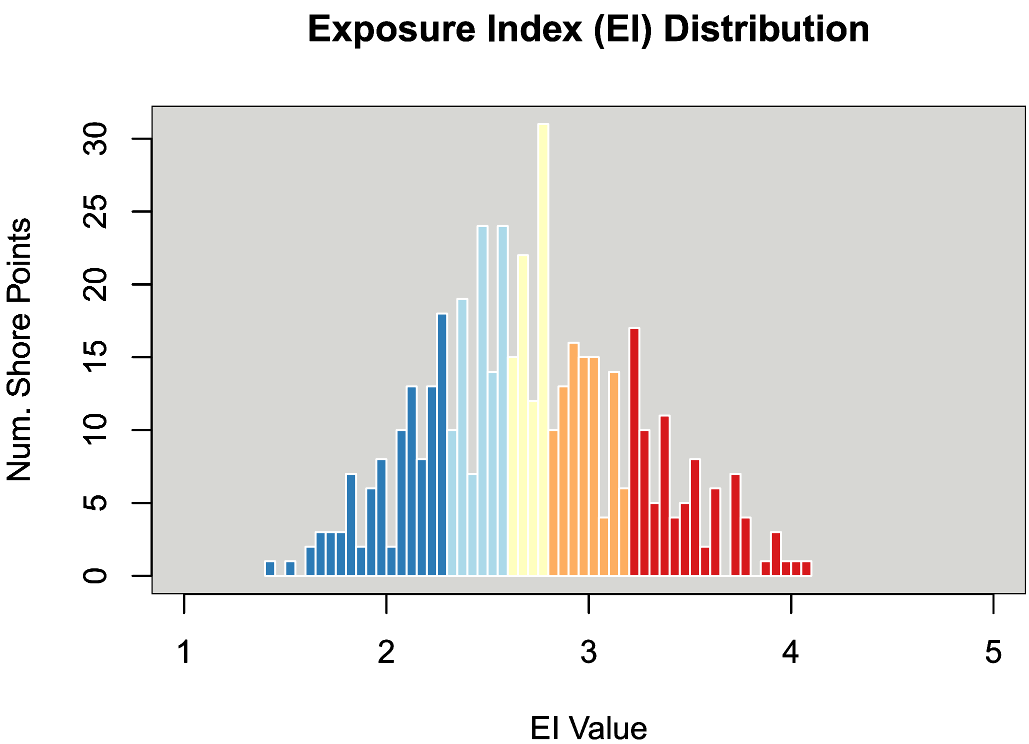

Figure 5. Distribution of the Exposure Index (EI). The plot is styled based on the 5 quantiles containing 20% of the distribution of the EI each. The colours are the same used in the maps presented in Figures 3 and 4.

Table 3. Summary statistics of the Exposure Index (EI) and the two *habitats* and *geomorphology* sub-indices for the current climate period (1991–2020).

Statistic	EI	Habitats	Geomorphology
Minimum	1.43	1.37	1
Maximum	4.06	5	5
Mean	2.71	3.12	2.87
Median	2.68	2.99	3
Standard Deviation	0.51	1.50	0.53

3.2. Outputs Pertaining to Individual Sub-Indices

The model output type allows to further investigate the main sub-index driver(s) behind the particularly high EI for the areas mentioned above. The very high exposure for several shore points in the Genoa port area can be in general traced back to a combination of absence of habitats potentially providing protection to the coast and a generally very low relief (port infrastructure at very low elevation above water). The model identifies shore points located directly on the breakwater protecting the entrance channel to the port as particularly exposed to waves as well.

For La Spezia, the low relief and lack of habitats still hold true. Moreover, in this instance the model identifies a relatively higher surge potential when compared to the rest of the AOI, due to the bigger distance between this city and the location of the continental shelf edge provided as input to the model.

Coastline stretches pertaining to the municipalities of Chiavari and Lavagna (east of the Portofino promontory) are at highest exposure due to particularly high values of the wind and wave sub-indices. It is worth noting the proximity of these municipalities to Rapallo, whose recorded extreme weather event in 2018 was referenced as a worst-case scenario situation to set model parameters. These findings are also consistent with S-SW (Libeccio) direction being associated to most coastal storms for Liguria [43].

Some sub-indices present a clustering behaviour in space. For instance, shore points ranking the worst in terms of the habitats sub-index are concentrated exclusively in proximity of the two main port areas of the region (Genoa and La Spezia), and those ranking worse in terms of surge potential are located exclusively in La Spezia. Shore points ranking the worst in terms of relief are scattered across the whole regional territory, but are consistently associated to port infrastructure at low elevation above water: for this reason, a lot of shore points of this type are located in the two main port areas of the region.

On the other hand, shore points that are more exposed due to climate variables show less of a spatial clustering behaviour. Shore points ranking badly in terms of wave power are mostly found scattered through the eastern part of the region (Genoa and La Spezia provinces). The same happens with regards to wind exposure, with the worst ranking shore points showing a more scattered distribution in space with still a bit of a prevalence in the eastern portion of the Region.

3.3. Model Outputs Validation

Validating the InVEST Coastal Vulnerability model outputs is a challenging task due to the aggregation of diverse data types and to the qualitative nature of the EI provided. Furthermore, flood risk appraisals are generally difficult to validate against real-life data due to the lack of recorded observations of extreme events location and consequences.

For this case study, an attempt of result validation was performed by comparing model outputs to coastal risk appraisals provided by the Ligurian regional administration in the framework of the *Piano di Tutela dell'Ambiente Marino Costiero* (PTAMC) [73] for some portions of the Ligurian coastline (*'ambiti'* 08-15-16-17-18). The regional administration ranking consisted of 4 ordinal categories. Coastline segments within the areas considered which were not associated to any risk according to the regional appraisal were considered to be at lowest risk for the purpose of this analysis. The regional ranking thus consisted of a total of 5 ordinal risk categories. Regional risk rankings were assigned to InVEST shore points through a spatial join with Voronoi diagram cells generated from InVEST shore points in a GIS environment. In case of multiple categories of the regional ranking pertaining to the same Voronoi cell, the ranking of the biggest shoreline segment was considered. Adopting the same ranking system the InVEST model utilises to assign sub-indices, the EI values associated to the shore points were transformed in 5 categories according to 5 quantiles containing 20% of the EI distribution each (for the whole sample of 457 points). Thus, each shore point was associated to both an InVEST ranking and a regional ranking. The validation subset consisted of 245 shore points out of the original 457 due to the reduced spatial extent of the regional risk appraisal. Table 4 shows a comparison of the two ranking systems considered.

Due to the ranking system adopted, shore points classified according to the InVEST model show an almost uniform distribution, with similar amounts of points falling into each category even when considering the validation sample. Conversely, the vast majority of shore points is at low risk according to the regional classification, and the highest risk is associated to very few points. Assuming the regional classification to better approximate the ground truth within this validation analysis, the InVEST model accuracy can be conveyed by looking at the number of points both appraisal methods classify in the same way. Considering shore points at lowest, low, high and highest risk approximately 32% of the points (79 out of 245) were correctly classified by the InVEST model (bottom-right and upper-left corners of the table) and approximately 40% of the points (98 out of 245) were misclassified.

Table 4. Validation of InVEST model results against coastal risk appraisals provided by the Regional Administration. Values in bold italics represent the shore points that are classified in the same way by the two methods considered as being at lowest, low, high and highest risk.

Regional Risk Classification	**InVEST Coastal Vulnerability Model Classification (EI)**					
	Lowest	Low	Intermediate	High	Highest	**Total Regional**
Lowest	***8***	***8***	9	7	11	43
Low	***19***	***23***	39	40	27	148
Intermediate	3	4	1	5	1	14
High	3	8	6	***5***	***15***	37
Highest	1	1	0	***0***	***1***	3
Total InVEST	34	44	55	57	55	245

3.4. Study of the Model's Sensitivity to Changes in Climate Data Inputs

Sensitivity analyses aim at assessing how variations in model inputs or parameters affect model outputs [74]. The sensitivity analysis presented here intends to highlight how changes in climate variables are *translated* into changes in the outcome vulnerability computed by the model, keeping all other input variables equal. Results of the sensitivity analysis of the InVEST Coastal Vulnerability model to variations in climate inputs are shown in Table 5.

The percentage of the number of shore points whose value undergoes variation from one climate period to the other is reported in the middle column. The column on the right shows the average variation from one climate period to the other (considering present values minus past values). Different rows are associated to subsequently more aggregate data types. The first row reports the simple interpolation of ERA5-derived climate data for wind and waves to the shore points generated by the model, which can be interpreted as raw data for wind speed (in m/s) and wave energy flux (kW/m). Intermediate outputs are computed by the model as a multiplication of the above-mentioned raw data by other factors such as time and fetch distance. The model then computes wind and wave sub-indices by arranging intermediate outputs in an ordered distribution and then allocating the values to 5 equal bins corresponding to 20% of the distribution each. The 5 bins obtained through this process correspond to ranks 1 to 5 and represent the sub-indices of exposure for wind and waves. The EI is computed by the model as described in Section 2.

These results highlight how the gradual aggregation of data performed by the model induces a progressively more marked masking of the variations in climate data pertaining to different periods. In the case of raw data simply interpolated to shore points before any further computation, all shore points undergo variations between the two climate periods, reflecting the changes in climate patterns. The same happens for intermediate outputs, yet the interpretation of the average variation between periods for these variables is hindered by the complex aggregation of several units of measurement (see [35]).

On the other hand, the ordering and binning process mask most of the variation, resulting in the vast majority of shore points not changing value between the two climate periods when considering both the sub-indices and the resulting EI. The binning procedure also masks the average variation for the wind and wave sub-indices: since two symmetrical variations are always generated, the average variation is always null.

The analyses presented here highlight the main hindrances to the use of the InVEST Coastal Vulnerability model to account for magnitude-of-effect questions [46], including those concerning varying climate scenarios. The data aggregation processes smooth over any variation in the original climate data to the point of rendering almost indistinguishable different climate periods. It might be argued that the original average variations of raw data between periods are of small magnitude to begin with, and that this could result in the lack of variation getting transmitted through the various aggregation steps within the model. Some smoothing in the climate data can indeed be attributed to the need to use periods of at least 5 years for climate data inputs, according to model specifications [35]. Further analyses might therefore need to focus on the creation of synthetic data of more extreme wind and waves to better test the sensitivity of the model to variations of a greater magnitude. Nevertheless, the low percentage of shore points undergoing variations between the two periods when considering the EI (below 5%) and the climate sub-indices (around 3.5% for wind and below 1% for waves) is still noteworthy, if compared to raw data (100% of shore points undergoing variations between periods). Such an asymmetry between raw data and vulnerability metrics represents a relevant methodology limitation, especially in the context of a spatially-explicit assessment methodology aiming to highlight the geographical roots of vulnerability such as the one used for this case study.

Table 5. Analysis of model sensitivity to variations in climate data inputs between the two 30-year climate periods spanning 1961–1990 and 1991–2020.

Variable	% Shore Points Undergoing Variation	Average Variation (Present–Past)
Wind Speed Interpolated to Shore Points (m/s)	100%	−0.14 m/s (−1.52%)
Wave Power Interpolated to Shore Points (kW/m)	100%	−0.79 kW/m (−6.5%)
Intermediate Model Output for Wind	100%	−42,345.77 (−12.6%)
Intermediate Model Output for Waves	100%	−0.126 (−4.96%)
Wind Sub—Index (range 1–5; integers only)	3.5%	0 (0%)
Wave Sub—Index (range 1–5; integers only)	0.87%	0 (0%)
Exposure Index (range 1–5)	4.37%	−0.0098 (−0.36%)

4. Discussion

In the Mediterranean Sea basin, atmospheric and ocean dynamics determining sea-level changes are appreciably regionally characterised with regards to the cyclogenesis areas location [75]. Additionally, the relative magnitude of the influence of wind and air pressure on sea levels is markedly significant in semi-enclosed sea basins, as tidal waves get substantially filtered out by straits and other morphological features [76]. Adapting the InVEST model to the Mediterranean Sea basin for the first time entailed tuning the model parameters to account for the much smaller fetch distances over which wind can potentially blow over water (see Section 2.6).

The model parameters also needed to be tuned with regards to the natural habitats of the region. The majority of literature dealing with the characterisation of the potential of coastal habitats to reduce inundation and other adverse impacts has so far focused on habitats that are not present in this geographical context, such as coral reefs, mangroves or kelp forests [68,77]. The coralligenous biocoenosis which is present in the area is akin to a coral reef, but knowledge on its distribution, biology and role within ecosystems is still fragmentary [70]. Other habitats whose flood mitigation potential has been better analysed such as coastal wetlands [6] exist in the Mediterranean Sea basin, though noteworthy instances thereof cannot be found in Liguria specifically [78].

This work aims at contributing to the development of research on exposure to coastal hazards by inquiring about the suitability of the methodology of choice to yield a good enough characterisation of the climate driver component behind the evolution of the coastal flood hazard. To that end, a focus was devoted to the climate data inputs. ERA5 reanalysis data was used as input to the model, instead of the default dataset WaveWatchIII which is suggested for use by model developers. A sensitivity analysis for climate data inputs was also carried out. Both the use of ERA5 data and the creation of different climate scenarios in order to test the InVEST Coastal Vulnerability sensitivity to variations in climate forcings represent novel contributions to research.

4.1. Scope of Application of the Methodology Used

Different choice portfolios can yield different benefit quantities, qualities and values. The InVEST Coastal Vulnerability model's main field of application is to inform spatial planning in the coastal zone by providing an analysis framework to help discern among decision trade-offs and better identify benefits to population associated to distinctive management choices [45]. The suite of InVEST models focuses primarily on bridging the disconnect between science and practice with regards to benefits to society provided by ecosystems, for instance by rendering explicit within the analysis their contribution to adaptation or mitigation to climate change [46,79]. Such models have been applied in contexts and for communities which have historically been particularly vulnerable to environmental or climate-related hazards, or whose livelihood is strongly tied to the existence and wellbeing of specific ecosystems [50]. Most InVEST models including Coastal Vulnerability were designed to allow use with broadly-available datasets. For this reason, they have found wide application in data-scarce contexts, where more in-depth appraisals might not be feasible or economically viable [3].

Research dealing with vulnerability assessments to climate change is characterised by a significant variety of approaches and a lack of generally agreed-upon best practices and frameworks, leading to a generalised difficulty in comparing research results and assessment outputs [2]. Maps and other communication and decision support tools for the operationalisation of assessment results vary as well [3,28]. This is also due to the high context-dependency of the concept of vulnerability itself, which is echoed by the need to adopt methodologies that are best fit for each specific situation [80].

Evaluating the adherence between vulnerability assessments and reality represents a particularly relevant literature shortcoming, highlighted by a generalised paucity of sensitivity and uncertainty analyses as well as validation efforts with regards to assessment results [3].

4.1.1. Potential of the Approach

The case for keeping into account all dimensions of vulnerability in a comprehensive framework for analysis has been proposed extensively in literature [2,3,80]. Though, this case study analysed the physical exposure component of (outcome) vulnerability exclusively [3,30], in order to focus on how to best account for climate patterns within this type of index-based methodology. The modular nature of the InVEST Coastal Vulnerability model has allowed to carry out the analysis even without the inclusion of socioeconomic data, focusing on the Exposure Index (EI) only.

The InVEST Coastal Vulnerability model is strongly characterised by its spatially-explicit character, providing insights on how and where in space different components of the socio-environmental system interact in determining the overall vulnerability or exposure within the territory. Thus, this approach allowed to take into account the site and context-specific nature of variables and processes contributing to vulnerability locally, which has been highlighted as an aspect of paramount importance in previous literature [46,81]. Both grey and green infrastructure are considered within the analysis, through the inclusion of data pertaining to shore-protection structures and information on local ecosystems.

Index-based approaches to flood vulnerability or exposure assessment such as the one proposed in this work have in general been found to provide relatively trustworthy yet rapid appraisals for specific locations [12,19], and mainly find application in identifying priority areas where action is most likely to add value. Differently from process-based methodologies, index-based approaches providing categorical metrics are not suitable for addressing questions of *magnitude-of-effect*, such as the quantification of the habitats' potential to reduce wave heights or current strengths. The choice of the type of approach depends on the questions that need answering and on the phase of policy implementation the appraisals are intended to support [46].

The work carried out for the development of this case study also aimed at better delineating the scope of application of index-based categorical approaches with regards to the inclusion on data on inherently dynamic climate processes. Do this type of methods provide a good enough representation of the *'ground truth'* upon which to orient policy attention? To what extent can their results be subject to validation? What is the scope to carrying out climate scenario analyses through them?

4.1.2. Limitations of the Approach

The case has been made in literature for adopting index-based approaches to coastal flood assessment in order to support solely some phases of the policy-making process and to answer some specific types of questions. Though, the question might still be raised on whether using this type of deterministic and categorical approach early on in the analysis process might result in appraisals that are approximate to the point of misleading the choice of which actions or research objectives to pursue later on.

In general, deterministic and static approaches to coastal flood assessment have shown to lead to substantial overestimation of flood impacts, and are usually considered suitable for first approximation, large-scale flood hazard mapping only [18,37]. Though, [14] highlighted how static approaches perform poorly even for large-scale appraisals, and stressed the need to adopt dynamic process-based methods.

Indicator-based approaches to vulnerability assessment require further inquiry with regards to the choice, aggregation and weighting criteria of diverse data sources into an individual measure [2,30]. Ramieri et al. [31] noted how index-based approaches expressing coastal vulnerability into a one-dimensional and unitless index such as the one provided by the InVEST Coastal Vulnerability model are generally not transparent, as the understanding of underlying assumptions behind the calculations is not conveyed by the final index [2]. As the support to decision-making processes is the core upon which such methodologies are built, the inability to accurately orient attention towards the contextual drivers of vulnerability is possibly the most relevant shortcoming of the approach adopted here.

This work has also described how the data arrangement and ranking procedures, as well as the type of index output by the model make such an approach unsuitable to depict changes in climate variables and thus does not allow to carry out meaningful climate scenarios. The categorical nature of the output index also hinders meaningful interpretations of the results in physical terms, thus limiting the type of result validation attempts available.

In its most established interpretation, exposure is understood as the inventory of elements potentially impacted by adverse events; since the InVEST Coastal Vulnerability model does not provide any information regarding the extent of the areas potentially inundated, no precise inventory of population and assets potentially exposed can be computed based on model outputs.

4.2. Future Developments

A lack of understanding of the dynamic interactions among the risk components has been addressed in the scientific community [82]. For this reason, future developments of this research will prioritise a better depiction of the interplay among the components of the coastal system leading to flood hazard development and unfolding. Ideally, the output of the analysis would be a projected flooded area extent given the climate conditions and local terrain features, in order to obtain results which could to some extent be subject to validation against observed data and used to support climate scenarios.

Methodologies in the field on machine learning (ML) have been shown to be able to capture complex interactions among relevant variables in flood-exposed systems and to resolve processes happening at different timescales [83]. ML is thus currently being used in literature to provide flood susceptibility assessments in a relatively quick and less computationally-intensive way when compared to traditional numerical flood modelling methodologies. Some attempts of applications in coastal areas have been made [83], though most literature proposing such methodologies has so far focused on pluvial and fluvial floods [84,85]. Future developments in this research will entail exploring ways to adopt ML-based techniques to study impacts of ESLs, including the choice of which relevant geomorphological and climate-related flood triggering factors to include in the analysis. The most likely hindrances within this research perspective are finding a methodology which allows a good interpretation of the most important features affecting the model [83], and the high data requirements for model training in the face of a paucity of well documented coastal inundation events [14].

5. Conclusions

The urgency and uncertainty of climate change-induced consequences on coastal communities, primarily in terms of coastal flooding, have resulted in the widespread request for and uptake of coastal vulnerability appraisals. This process has been supported by a flourishing of frameworks and assessment methodologies developed for such a purpose, to the point of bringing about a lack in standardisation and a frequently hasty or inadequate application of best research practices.

Within this context, this work is aimed at studying the suitability of index-based methodologies for coastal vulnerability to accurately convey information on observed variations in climate variables contributing to the generation of Extreme Sea Levels (ESLs) in coastal areas. This research objective is investigated through a case study assessment of the physical exposure component of coastal vulnerability to inundation and erosion for the Italian coastal region Liguria.

The InVEST Coastal Vulnerability model [34] was used within the study area in order to obtain a version of the Coastal Vulnerability Index (CVI) [22,23], based on the aggregation of data on several biogeophysical variables. Particular attention was devoted to the data pertaining to wind speed and wave power; ERA5 reanalysis data [36] was used for the first time to run this model, and two different climate periods were reconstructed from the reanalysis dataset in order to test two climate scenarios within the model.

The results of this case study analysis substantiate previous literature findings regarding index-based methodologies being an advantageous choice in terms of yielding a comprehensive preliminary grasp of coastal vulnerability locally, while still allowing a relative velocity of use, low data input needs and little computational requirements. Most of all, the InVEST Costal Vulnerability model outputs show to be in somewhat good accordance with observed geomorphological characteristics, correctly identifying in space areas most vulnerable because of low elevation above water, specific shoreline type or local bathymetric features.

Nevertheless this work further contributes to emphasise how methodology issues pertaining to data choice, aggregation and indicator computation can impair some applications of coastal vulnerability assessments, particularly regarding the inclusion of climate change variations within the analysis. Within this particular approach, the data aggregation process results in an almost complete loss of the original information conveyed by raw data on climate variables. This results in the unsuitability of this method to accurately reproduce past observed changes or carry out *what-if* scenarios of climate conditions which might result in ESLs, in support of policymaking processes.

This work originally contributes to literature delineating the perimeter of application of different vulnerability assessment methodologies, by providing an in-depth investigation of the opportunities and drawbacks related to the inclusion within the analysis of data on inherently dynamic climate-change processes.

It suggests that some indicator-based methodologies might produce misleading results if information is not adequately supported by sensitivity analyses and results validation. It further argues that future research in the field should carefully consider the consequences of the methodology of choice on the outcome representation of climate-change impacts, most notably in instances when research outcomes are intended to be used to inform concrete action such as climate adaptation plans for coastal communities and related economic valuations.

Author Contributions: Conceptualization, A.R., L.M. and A.P.; methodology, A.R., L.M. and A.P.; formal analysis, A.R. and L.M.; investigation, A.R. and L.M.; data curation, A.R., L.M. and A.P.; writing—original draft preparation, A.R.; writing—review and editing, A.R., L.M. and A.P.; visualization, A.R.; supervision, L.M. and A.P.; funding acquisition, L.M. and A.P. All authors have read and agreed to the published version of the manuscript.

Funding: Lorenzo Minola is funded by the International Postdoc grant from the Swedish Research Council (2021-00444).

Data Availability Statement: Publicly available datasets were analyzed in this study. Links to the data repositories utilised are reported in Table 1.

Acknowledgments: The authors wish to thank Carlotta Quagliolo (Politecnico and Università di Torino) for the helpful insights on the study area and for the support in setting up the study design. The authors also wish to thank Professor Alessandro Toffoli (University of Melbourne) for the help in obtaining wave data from the ERA5 reanalysis.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

GMSL	Global mean Sea Level
ESL	Extreme Sea Level
RCP	Representative Concentration Pathway
EU	European Union
NBS	Nature-Based Solutions
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
EI	Exposure Index
CVI	Coastal Vulnerability Index
AOI	Area of Interest
DEM	Digital Elevation Model

DBM	Digital Bathymetry Model
ECMWF	European Centre for Medium-Range Weather Forecasts
EMODnet	European Marine Observation and Data Network
GEBCO	General Bathymetric Chart of the Oceans
ML	Machine Learning

Appendix A

Table A1. Ranks assigned to the geomorphology data input used for the case study.

Shore Class	Shore Sub-Class	Rank
Artificial Coastline	Shore-Parallel Hard Structures (Above Sea Level)	2
Artificial Coastline	Not Specified	3
Estuary/River Mouth	Not Specified	4
Gravel	Not Specified	4
Rock	Low-lying Rocky Shore	3
Rock	High Cliffs	1
Rock	Not Specified	2
Sand	Not Specified	5
Harbour Limits	Not Specified	3
Submerged Breakwaters	Adherent or Parallel to the Shore	3

Table A2. Ranks assigned to the habitats data input used for the case study. In this case study, the *protection distance* parameter was derived through the approach suggested by model developers for cases where there is limited published literature regarding the distance at which habitats can provide protection to the coastline [35]. The values in the middle column therefore reflect the average distance between the location of a given habitat and the shoreline in the given AOI.

Habitat Name	Protection Distance [m]	Rank
Coralligenous Biocoenosis	2000	1
Cymodocea Nodosa	800	3
Posidonia Oceanica (Neptune Grass)	1200	3
Caulerpa	500	4
Sciaphilous Algae	100	4
Photophilic Algae	150	4

References

1. Oppenheimer, M.; Glavovic, B.; Hinkel, J.; van de Wal, R.; Magnan, A.; Abd-Elgawad, A.; Cai, R.; Cifuentes-Jara, M.; DeConto, R.; Ghosh, T.; et al. Sea Level Rise and Implications for Low-Lying Islands, Coasts and Communities. In *IPCC Special Report on the Ocean and Cryosphere in a Changing Climate*; IPCC Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2019.
2. Nguyen, T.T.; Bonetti, J.; Rogers, K.; Woodroffe, C.D. Indicator-based assessment of climate-change impacts on coasts: A review of concepts, methodological approaches and vulnerability indices. *Ocean Coast. Manag.* **2016**, *123*, 18–43. . [CrossRef]
3. Bukvic, A.; Rohat, G.; Apotsos, A.; de Sherbinin, A. A Systematic Review of Coastal Vulnerability Mapping. *Sustainability* **2020**, *12*, 2822. [CrossRef]
4. Moatti, J.P.; Thiébault, S. (Eds.) *The Mediterranean Region Under Climate Change. A Scientific Update* ; IRD Éditions: Marseille, France, 2016.
5. Ali, E.; Cramer, W.; Carnicer, J.; Georgopoulou, E.; Hilmi, N.; Le Cozannet, G.; Lionello, P. Cross-Chapter Paper 4: Mediterranean Region. In *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2022.
6. Nicholls, R.J.; Hoozemans, F.M.; Marchand, M. Increasing flood risk and wetland losses due to global sea-level rise: Regional and global analyses. *Glob. Environ. Chang.* **1999**, *9*, S69–S87. [CrossRef]
7. Marcos, M.; Jordà, G.; Gomis, D.; Pérez, B. Changes in storm surges in southern Europe from a regional model under climate change scenarios. *Glob. Planet. Chang.* **2011**, *77*, 116–128. [CrossRef]
8. Conte, D.; Lionello, P. Characteristics of large positive and negative surges in the Mediterranean Sea and their attenuation in future climate scenarios. *Glob. Planet. Chang.* **2013**, *111*, 159–173. [CrossRef]
9. Lionello, P.; Cogo, S.; Galati, M.; Sanna, A. The Mediterranean surface wave climate inferred from future scenario simulations. *Glob. Planet. Chang.* **2008**, *63*, 152–162. [CrossRef]

10. IPCC. IPCC Common Methodology (CM). Update provided in Appendix C in IPCC CZMS, 1992. In *Global Climate Change and the Rising Challenge of the Sea*; Report of the Coastal Zone Management Subgroup; IPCC Response Strategies Working Group, Rijkswaterstaat: The Hague, The Netherlands, 1991.
11. Field, C.; Barros, V.; Dokken, D.; Mach, K.; Mastrandrea, M.; Bilir, T.; Chatterjee, M.; Ebi, Y.; Estrada, Y.; Genova, R.; et al. IPCC, 2014: Summary for Policymakers. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. In *Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; IPCC: Geneva, Switzerland, 2014.
12. Bigi, V.; Comino, E.; Fontana, M.; Pezzoli, A.; Rosso, M. Flood Vulnerability Analysis in Urban Context: A Socioeconomic Sub-Indicators Overview. *Climate* **2021**, *9*, 121. [CrossRef]
13. Vousdoukas, M.I.; Mentaschi, L.; Voukouvalas, E.; Bianchi, A.; Dottori, F.; Feyen, L. Climatic and socioeconomic controls of future coastal flood risk in Europe. *Nat. Clim. Chang.* **2012**, *8*, 776–780. [CrossRef]
14. Vousdoukas, M.I.; Voukouvalas, E.; Mentaschi, L.; Dottori, F.; Giardino, A.; Bouziotas, D.; Bianchi, A.; Salamon, P.; Feyen, L. Developments in large-scale coastal flood hazard mapping. *Nat. Hazards Earth Syst. Sci.* **2016**, *16*, 1841–1853. [CrossRef]
15. Tebaldi, C.; Strauss, B.H.; Zervas, C.E. Modelling sea level rise impacts on storm surges along US coasts. *Environ. Res. Lett.* **2012**, *7*, 014032. [CrossRef]
16. Jongman, B.; Ward, P.J.; Aerts, J.C. Global exposure to river and coastal flooding: Long term trends and changes. *Glob. Environ. Chang.* **2012**, *22*, 823–835. [CrossRef]
17. Vousdoukas, M.; Mentaschi, L.; Voukouvalas, E.; Feyen, L. PESETA III, Task 8: Coastal Impacts. In *Technical Report LB-NA-28243-EN-N*; Publications Office of the European Union: Luxembourg, 2019.
18. Gallien, T.; Sanders, B.; Flick, R. Urban coastal flood prediction: Integrating wave overtopping, flood defenses and drainage. *Coast. Eng.* **2014**, *91*, 18–28. [CrossRef]
19. Nasiri, H.; Mohd Yusof, M.J.; Mohammad Ali, T.A. An overview to flood vulnerability assessment methods. *Sustain. Water Resour. Manag.* **2016**, *2*, 331–336. [CrossRef]
20. Abuodha, P.A.; Woodroffe, C.D. 12 Vulnerability assessment. In *Coastal Zone Management*; Thomas Telford Limited: London, UK, 2015; pp. 262–290. [CrossRef]
21. Torresan, S.; Critto, A.; Rizzi, J.; Marcomini, A. Assessment of coastal vulnerability to climate change hazards at the regional scale: The case study of the North Adriatic Sea. *Nat. Hazards Earth Syst. Sci.* **2012**, *12*, 2347–2368. [CrossRef]
22. Gornitz, V. Vulnerability of the East Coast, U.S.A. to Future Sea Level Rise. *J. Coast. Res.* **1990**, *9*, 201–237.
23. Hammar-Klose, E.S.; Thieler, E.R. *Coastal Vulnerability to Sea-Level Rise: A Preliminary Database for the U.S. Atlantic, Pacific, and Gulf of Mexico Coasts*; U.S. Geological Survey: Reston, VA, USA, 2001. [CrossRef]
24. Boruff, B.J.; Emrich, C.; Cutter, S.L. Erosion Hazard Vulnerability of US Coastal Counties. *J. Coast. Res.* **2005**, *2005*, 932–942. [CrossRef]
25. Cutter, S.L.; Boruff, B.J.; Shirley, W.L. Social Vulnerability to Environmental Hazards*. *Soc. Sci. Q.* **2003**, *84*, 242–261. [CrossRef]
26. Balica, S.F.; Wright, N.G.; van der Meulen, F. A flood vulnerability index for coastal cities and its use in assessing climate change impacts. *Nat. Hazards* **2012**, *64*, 73–105. [CrossRef]
27. Skoulikaris, C.; Makris, C.; Katirtzidou, M.; Baltikas, V.; Krestenitis, Y. Assessing the Vulnerability of a Deltaic Environment due to Climate Change Impact on Surface and Coastal Waters: The Case of Nestos River (Greece). *Environ. Model. Assess.* **2021**, *26*, 459–486. [CrossRef]
28. de Sherbinin, A.; Bukvic, A.; Rohat, G.; Gall, M.; McCusker, B.; Preston, B.; Apotsos, A.; Fish, C.; Kienberger, S.; Muhonda, P.; et al. Climate vulnerability mapping: A systematic review and future prospects. *WIREs Clim. Chang.* **2019**, *10*, e600. [CrossRef]
29. Molinari, D.; De Bruijn, K.M.; Castillo-Rodríguez, J.T.; Aronica, G.T.; Bouwer, L.M. Validation of flood risk models: Current practice and possible improvements. *Int. J. Disaster Risk Reduct.* **2019**, *33*, 441–448. [CrossRef]
30. Füssel, H.M. *Review and Quantitative Analysis of Indices of Climate Change Exposure, Adaptive Capacity, Sensitivity, and Impacts*; The World Bank: Washington DC, USA, 2010.
31. Ramieri, E.; Hartley, A.; Barbanti, A.; Duarte Santos, F.; Gomes, A.; Hilden, M.; Laihonen, P.; Marinova, N.; Santini, M. *Methods for Assessing Coastal Vulnerability to Climate Change*; ETC/CCA Technical Paper I-40127: Bologna, Italy, 2011.
32. Quagliolo, C.; Comino, E.; Pezzoli, A. Experimental Flash Floods Assessment Through Urban Flood Risk Mitigation (UFRM) Model: The Case Study of Ligurian Coastal Cities. *Front. Water* **2021**, *3*. [CrossRef]
33. Regione Liguria. Interventi Straordinari e di Emergenza. Available online: https://www.regione.liguria.it/homepage-attivita-istituzionale/trasparenza/amministrazione-trasparente/interventi-straordinari-e-di-emergenza.html (accessed on 20 January 2023).
34. Sharp, R.; Douglass, S.; Wolny, S.; Arkema, K.; Bernhardt, J.; Bierbower, W.; Chaumont, N.; Denu, D.; Fisher, D.; Glowinski, K.; et al. *InVEST User Guide*; The Natural Capital Project; Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund: Stanford, CA, USA, 2020.
35. InVEST User Guide. Available online: http://releases.naturalcapitalproject.org/invest-userguide/latest/coastal_vulnerability.html (accessed on 2 December 2022).
36. Hersbach, H.; Bell, B.; Berrisford, P.; Hirahara, S.; Horányi, A.; Muñoz-Sabater, J.; Nicolas, J.; Peubey, C.; Radu, R.; Schepers, D.; et al. The ERA5 global reanalysis. *Q. J. R. Meteorol. Soc.* **2020**, *146*, 1999–2049. [CrossRef]

37. Gallien, T.W.; Kalligeris, N.; Delisle, M.P.C.; Tang, B.X.; Lucey, J.T.D.; Winters, M.A. Coastal Flood Modeling Challenges in Defended Urban Backshores. *Geosciences* **2018**, *8*, 450. [CrossRef]
38. Italian National Institute of Statistics (ISTAT). Popolazione residente al 1 Gennaio 2022. Available online: https://demo.istat.it/app/?i=POS&l=it (accessed on 24 October 2022).
39. Agenzia Regionale per la Protezione dell'Ambiente Ligure (ARPAL). Atlante Climatico della Liguria. Available online: https://www.arpal.liguria.it/contenuti_statici/clima/atlante/Atlante_climatico_della_Liguria.pdf (accessed on 26 October 2022).
40. Piano Nazionale di Adattamento ai Cambiamenti Climatici (PNACC), 2018. Available online: https://www.mite.gov.it/sites/default/files/archivio/allegati/clima/pnacc.pdf (accessed on 25 October 2022).
41. Fratianni, C.; Pinardi, N.; Lalli, F.; Simoncelli, S.; Coppini, G.; Pesarino, V.; Bruschi, A.; Cassese, M.; Drudi, M. Operational oceanography for the Marine Strategy Framework Directive: the case of the mixing indicator. *J. Oper. Oceanogr.* **2016**, *9*, s223–s233. [CrossRef]
42. Rete Mareografica Nazionale. Available online: https://www.mareografico.it/?session=0S1164445412ETER72BHD&syslng=ita&sysmen=-1&sysind=-1&syssub=-1&sysfnt=0&code=STAZ&idst=2G (accessed on 25 October 2022).
43. Regione Liguria. Piano di Tutela dell'Ambiente Marino e Costiero. Relazione sul Clima Ondoso al Largo (RO). Available online: https://www.regione.liguria.it/component/publiccompetitions/document/40334.html?view=document&id=40334:relazione-sul-clima-ondoso-al-largo-ro&Itemid=4630 (accessed on 26 October 2022).
44. Agenzia Regionale per la Protezione dell'Ambiente Ligure (ARPAL). Riassunto Meteorologico Mensile. Ottobre 2018. Available online: https://www.arpal.liguria.it/contenuti_statici/pubblicazioni/rapporti_mensili/2018/201810_ottobre_meteo.pdf (accessed on 11 January 2023).
45. Guerry, A.D.; Ruckelshaus, M.H.; Arkema, K.K.; Bernhardt, J.R.; Guannel, G.; Kim, C.K.; Marsik, M.; Papenfus, M.; Toft, J.E.; Verutes, G.; et al. Modeling benefits from nature: Using ecosystem services to inform coastal and marine spatial planning. *Int. J. Biodivers. Sci. Ecosyst. Serv. Manag.* **2012**, *8*, 107–121. [CrossRef]
46. Ruckelshaus, M.H.; Guannel, G.; Arkema, K.; Verutes, G.; Griffin, R.; Guerry, A.; Silver, J.; Faries, J.; Brenner, J.; Rosenthal, A. Evaluating the Benefits of Green Infrastructure for Coastal Areas: Location, Location, Location. *Coast. Manag.* **2016**, *44*, 504–516. [CrossRef]
47. Ballesteros, C.; Esteves, L.S. Integrated Assessment of Coastal Exposure and Social Vulnerability to Coastal Hazards in East Africa. *Estuaries Coasts* **2021**, *44*, 2056–2072. [CrossRef] [PubMed]
48. Hopper, T.; Meixler, M.S. Modeling Coastal Vulnerability Through Space and Time. *PLoS ONE* **2016**, *11*, e0163495. [CrossRef]
49. Cunha, J.; Cardona, F.S.; Bio, A.; Ramos, S. Importance of Protection Service Against Erosion and Storm Events Provided by Coastal Ecosystems Under Climate Change Scenarios. *Front. Mar. Sci.* **2021**, *8*. [CrossRef]
50. Silver, J.M.; Arkema, K.K.; Griffin, R.M.; Lashley, B.; Lemay, M.; Maldonado, S.; Moultrie, S.H.; Ruckelshaus, M.; Schill, S.; Thomas, A.; et al. Advancing Coastal Risk Reduction Science and Implementation by Accounting for Climate, Ecosystems, and People. *Front. Mar. Sci.* **2019**, *6*, 1–19. [CrossRef]
51. Vrdoljak, L. Comparison and Analysis of Publicly Available Bathymetry Models in the East Adriatic Sea. *Naše More* **2021**, *68*, 110–119. [CrossRef]
52. Hersbach, H.; de Rosnay, P.; Bell, B.; Schepers, D.; Simmons, A.; Soci, C.; Abdalla, S.; Alonso-Balmaseda, M.; Balsamo, G.; Bechtold, P.; et al. Operational global reanalysis: Progress, future directions and synergies with NWP. In *ERA Report Series*; European Centre for Medium Range Weather Forecasts: Reading, UK, 2018. [CrossRef]
53. Minola, L.; Zhang, F.; Azorin-Molina, C.; Pirooz, A.A.S.; Flay, R.G.J.; Hersbach, H.; Chen, D. Near-surface mean and gust wind speeds in ERA5 across Sweden: Towards an improved gust parametrization. *Clim. Dyn.* **2020**, *55*, 887–907. [CrossRef]
54. Chiaravalloti, F.; Caloiero, T.; Coscarelli, R. The Long-Term ERA5 Data Series for Trend Analysis of Rainfall in Italy. *Hydrology* **2022**, *9*, 18. [CrossRef]
55. Barbariol, F.; Davison, S.; Falcieri, F.M.; Ferretti, R.; Ricchi, A.; Sclavo, M.; Benetazzo, A. Wind Waves in the Mediterranean Sea: An ERA5 Reanalysis Wind-Based Climatology. *Front. Mar. Sci.* **2021**, *8*. [CrossRef]
56. Vannucchi, V.; Taddei, S.; Capecchi, V.; Bendoni, M.; Brandini, C. Dynamical Downscaling of ERA5 Data on the North-Western Mediterranean Sea: From Atmosphere to High-Resolution Coastal Wave Climate. *J. Mar. Sci. Eng.* **2021**, *9*, 208. [CrossRef]
57. European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5: How to Calculate Wind Speed and Wind Direction from u and v Components of the Wind? Available online: http://confluence.ecmwf.int/pages/viewpage.action?pageId=133262398 (accessed on 27 October 2022).
58. Rusu, L.; Rusu, E. Evaluation of the Worldwide Wave Energy Distribution Based on ERA5 Data and Altimeter Measurements. *Energies* **2021**, *14*, 394. [CrossRef]
59. Thomas, G. Wave Power—The Theory Behind Ocean Waves. AZoCleantech, 2012. Available online: https://www.azocleantech.com/article.aspx?ArticleID=227 (accessed on 22 February 2022).
60. European Environment Agency (EEA). Reference Maps of SLR Projections for Europe. Available online: https://www.eea.europa.eu/ims/global-and-european-sea-level-rise (accessed on 5 December 2022).
61. Brázdil, R.; Zahradníček, P.; Dobrovolný, P.; Řehoř, J.; Trnka, M.; Lhotka, O.; Štěpánek, P. Circulation and Climate Variability in the Czech Republic between 1961 and 2020: A Comparison of Changes for Two Normal Periods. *Atmosphere* **2022**, *13*, 137. [CrossRef]

62. World Meteorological Organization (WMO). *WMO Guidelines on the Calculation of Climate Normals*, 2017 ed.; WMO report No. 1203; WMO: Geneva, Switzerland, 2017.
63. Seddon, N.; Chausson, A.; Berry, P.; Girardin, C.A.J.; Smith, A.; Turner, B. Understanding the value and limits of nature-based solutions to climate change and other global challenges. *Philos. Trans. R. Soc. B Biol. Sci.* **2020**, *375*, 20190120. [CrossRef]
64. Costanza, R.; Pérez-Maqueo, O.; Martinez, M.L.; Sutton, P.; Anderson, S.J.; Mulder, K. The value of coastal wetlands for hurricane protection. *Ambio* **2008**, *37*, 241–248. [CrossRef]
65. Barbier, E.B.; Hacker, S.D.; Kennedy, C.; Koch, E.W.; Stier, A.C.; Silliman, B.R. The value of estuarine and coastal ecosystem services. *Ecol. Monogr.* **2011**, *81*, 169–193. [CrossRef]
66. Arkema, K.; Guannel, G.; Verutes, G.; Wood, S.A.; Ruckelshaus, M.; Kareiva, P.; Lacayo, M.; Silver, J.M. Coastal habitats shield people and property from sea-level rise and storms. *Nat. Clim. Chang.* **2013**, *3*, 913–918. [CrossRef]
67. James, R.K.; Lynch, A.; Herman, P.M.J.; van Katwijk, M.M.; van Tussenbroek, B.I.; Dijkstra, H.A.; van Westen, R.M.; van der Boog, C.G.; Klees, R.; Pietrzak, J.D.; et al. Tropical Biogeomorphic Seagrass Landscapes for Coastal Protection: Persistence and Wave Attenuation During Major Storms Events. *Ecosystems* **2021**, *24*, 301–318. [CrossRef]
68. Guannel, G.; Arkema, K.; Ruggiero, P.; Verutes, G. The Power of Three: Coral Reefs, Seagrasses and Mangroves Protect Coastal Regions and Increase Their Resilience. *PLoS ONE* **2016**, *11*, e0158094. [CrossRef] [PubMed]
69. Serra, T.; Gracias, N.; Hendriks, I.E. Fragmentation in Seagrass Canopies Can Alter Hydrodynamics and Sediment Deposition Rates. *Water* **2020**, *12*, 3473. [CrossRef]
70. Ingrosso, G.; Abbiati, M.; Badalamenti, F.; Bavestrello, G.; Belmonte, G.; Cannas, R.; Benedetti-Cecchi, L.; Bertolino, M.; Bevilacqua, S.; Bianchi, C.N.; et al. Mediterranean Bioconstructions Along the Italian Coast. *Adv. Mar. Biol.* **2018**, *79*, 61–136. [CrossRef]
71. Realizzazione Della Nuova Diga Foranea di Genova Ambito Bacino di Sampierdarena. Volume 5—Studio Meteomarino. Available online: https://dpdigaforanea.it/wp-content/uploads/MI046R-PF-D-Z-R-005-01_STUDIO%20METEOMARINO.pdf (accessed on 26 April 2022).
72. GEBCO Bathymetric Compilation Group (2020). The GEBCO 2020 Grid—A Continuous Terrain Model of the Global Oceans and Land. Available online: https://doi.org/10.5285/a29c5465-b138-234d-e053-6c86abc040b9 (accessed on 30 May 2022).
73. Piano di Tutela dell'Ambiente Marino e Costiero (PTAMC). Available online: https://www.regione.liguria.it/homepage-ambiente/cosa-cerchi/acqua/mare-e-costa/competenze-regione/piano-di-tutela-dell-ambiente-marino-costiero.html (accessed on 30 November 2022).
74. Bennett, N.D.; Croke, B.F.; Guariso, G.; Guillaume, J.H.; Hamilton, S.H.; Jakeman, A.J.; Marsili-Libelli, S.; Newham, L.T.; Norton, J.P.; Perrin, C.; et al. Characterising performance of environmental models. *Environ. Model. Softw.* **2013**, *40*, 1–20. [CrossRef]
75. Lionello, P.; Barriopedro, D.; Ferrarin, C.; Nicholls, R.J.; Orlić, M.; Raicich, F.; Reale, M.; Umgiesser, G.; Vousdoukas, M.; Zanchettin, D. Extreme floods of Venice: Characteristics, dynamics, past and future evolution (review article). *Nat. Hazards Earth Syst. Sci.* **2021**, *21*, 2705–2731. [CrossRef]
76. Rutgersson, A.; Kjellström, E.; Haapala, J.; Stendel, M.; Danilovich, I.; Drews, M.; Jylhä, K.; Kujala, P.; Larsén, X.G.; Halsnæs, K.; et al. Natural hazards and extreme events in the Baltic Sea region. *Earth Syst. Dyn.* **2022**, *13*, 251–301. [CrossRef]
77. Gaylord, B.; Rosman, J.H.; Reed, D.C.; Koseff, J.R.; Fram, J.; MacIntyre, S.; Arkema, K.; McDonald, C.; Brzezinski, M.A.; Largier, J.L.; et al. Spatial patterns of flow and their modification within and around a giant kelp forest. *Limnol. Oceanogr.* **2007**, *52*, 1838–1852. [CrossRef]
78. Tinelli, A.; Folleto, A.; Frattarelli, F.; Maffei, L.; Musicanti, A.; Recanatesi, F. *Le Zone Umide*; Accademia Nazionale delle Scienze detta dei Quaranta: Roma, Italy, 2012; pp. 16–22.
79. Arkema, K.K.; Abramson, S.C.; Dewsbury, B.M. Marine ecosystem-based management: From characterization to implementation. *Front. Ecol. Environ.* **2006**, *4*, 525–532. [CrossRef]
80. Hinkel, J.; Bisaro, A. Methodological choices in solution-oriented adaptation research: A diagnostic framework. *Reg. Environ. Chang.* **2016**, *16*, 7–20. [CrossRef]
81. Weis, S.W.M.; Agostini, V.N.; Roth, L.M.; Gilmer, B.; Schill, S.R.; Knowles, J.E.; Blyther, R. Assessing vulnerability: An integrated approach for mapping adaptive capacity, sensitivity, and exposure. *Clim. Chang.* **2016**, *136*, 615–629. [CrossRef]
82. Reisinger, A.; Howden, M.; Vera, C.; Garschagen, M.; Hurlbert, M.; Kreibiehl, S.; Mach, K.J.; Mintenbeck, K.; O'Neill, B.; Pathak, M.; et al. *The Concept of Risk in the IPCC Sixth Assessment Report. A Summary of Cross-Working Group Discussions*; Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2020.
83. Zanetti, M.; Allegri, E.; Sperotto, A.; Torresan, S.; Critto, A. Spatio-temporal cross-validation to predict pluvial flood events in the Metropolitan City of Venice. *J. Hydrol.* **2022**, *612*, 128150. [CrossRef]
84. Chen, J.; Huang, G.; Chen, W. Towards better flood risk management: Assessing flood risk and investigating the potential mechanism based on machine learning models. *J. Environ. Manag.* **2021**, *293*, 112810. [CrossRef]
85. Wang, Y.; Fang, Z.; Hong, H.; Peng, L. Flood susceptibility mapping using convolutional neural network frameworks. *J. Hydrol.* **2020**, *582*, 124482. [CrossRef]

A Machine Learning Approach to the Identification of Areas Susceptible to Compound Coastal Flooding

Alice Re[1*], Lorenzo Minola[1,2,3], Gustau Camps-Valls[4], Alessandro Pezzoli[1]

[1*]Interuniversity Department of Regional and Urban Studies and Planning (DIST), Politecnico and University of Turin, Turin, Italy.
[2]Regional Climate Group, Department of Earth Sciences, University of Gothenburg, Gothenburg, Sweden.
[3]Centro de Investigaciones sobre Desertificación, Consejo Superior de Investigaciones Científicas (CIDE, CSIC-UV-Generalitat Valenciana), Climate, Atmosphere and Ocean Laboratory (Climatoc-Lab), Moncada, Valencia, Spain.
[4]Image Processing Laboratory (IPL), Universitat de València, València, Spain.

*Corresponding author(s). E-mail(s): alice.re@polito.it;

Abstract

This study presents a data-driven approach to assessing flood susceptibility in Liguria, a coastal region in the northwestern Mediterranean, where interactions between marine and fluvial systems heighten flood risks due to climate change. Using outputs from numerical flood models as ground truth, machine learning methods—including Support Vector Machines (SVM), Random Forest (RF), and U-Net convolutional neural networks—were employed to classify areas prone to compound flooding. Among these, RF models achieved the highest performance, with a precision of 0.81, recall of 0.84, and F1 score of 0.82 when applied at the individual watershed level. The simpler SVM models showed moderate performance (F1 score of 0.66), while U-Net models underperformed (F1 score of 0.06), likely due to overfitting. The RF models effectively captured topographic and hydrological patterns, especially in complex terrains, but performance diminished in flatter coastal areas. These results highlight the utility of RF as a surrogate model for rapid flood susceptibility assessment, particularly in data-scarce regions. The study has significant implications for flood risk management and climate adaptation planning. Despite limited data, it demonstrates that data-driven approaches can support first-order identification of flood-prone areas, which is crucial for early warning systems, urban planning, and resource allocation. Additionally, integrating machine learning with traditional flood modelling can enhance predictive accuracy while reducing computational overhead, offering a scalable solution for broader regional or global applications, particularly in coastal zones facing increasing flood risks.

Keywords: climate risk, coastal flood, compound flood, flood susceptibility, machine learning

1 Introduction

Climate change-related consequences in terms of long-term sea level rise and increases in storminess and extreme sea levels (Vousdoukas et al., 2018; Hinkel et al., 2021; Tebaldi et al., 2021), combined with processes of erosion and land subsidence (Syvitski et al., 2009; Nicholls and Cazenave, 2010) pose significant threats to coastal regions (Green et al., 2024). Urgent action is needed worldwide for risk management and climate change adaptation of coastal communities (Déguénon et al., 2024), especially in light of their high urbanisation and population growth rates (Bouwer, 2011; Jongman et al., 2012; Neumann et al., 2015), which could potentially result in high exposure to hazardous events and significant economic losses in the future (Hallegatte et al., 2013).

Because of their location at the intersection between marine and land systems (Cramer and Guiot, 2020), coastal zones can be affected by a combination of fluvial, pluvial and coastal flood drivers (Green et al., 2024). During compound flood events, extreme impacts may arise from the joint occurrence of several flood drivers, even if these drivers are not extreme in themselves (Bevacqua et al., 2017). The study of compound flooding is currently very active because of the need to better understand them from a statistical point of view (Bevacqua et al., 2017; Wu et al., 2018, 2021; Bevacqua et al., 2021) as well as in terms of their spatial patterns in complex coastal and estuarine regions (Bilskie and Hagen, 2018; Eilander et al., 2023; Mitu et al., 2023; Gao et al., 2023).

Among the world's coastal areas, the Mediterranean Sea basin is considered a climate change hotspot and has drawn attention in research because of its location in a transition zone between mid-latitude and sub-tropical atmospheric circulation regimes (Cramer et al., 2018; Sarkar et al., 2022). The basin is characterised as a micro-tidal area in which the near absence of tides has led to the establishment of dense urban settlements located just above the current sea levels and - as such - exposed to risks related to increased sea levels (Cramer and Guiot, 2020). Such risks are particularly relevant for the Italian region of Liguria, a narrow coastal area between the mountains and the sea in the Northwestern Mediterranean basin. The combination of local topography with high population density and severe soil sealing has led to the region being affected by pluvial, fluvial and coastal floods, both historically and with increasing frequency in recent times (Quagliolo et al., 2021; Brandolini et al., 2012; Garnier et al., 2018). As it pertains to pluvial and fluvial floods in the area, the regional topography and geomorphology and their interaction with water runoff and river discharges in the determination of floods and landslide hazards have been studied extensively (Brandolini and Terranova, 1994). Extreme sea levels and strong winds associated with storms in the recent past (the most relevant of which dates to October 2018) have caused significant damage to some coastal infrastructure and ecosystems within the region (Oprandi et al., 2020; Ferrando et al., 2021; Re et al., 2023, 2024). Within this context, recent literature has dealt with the characterisation of coastal geomorphology (Pesci et al., 2016; Colangeli et al., 2023), wave climate and coastal hydrodynamics for some specific near-shore portions of the regional coastal waters (Federici et al., 2019; Guarnieri et al., 2021; Vannucchi et al., 2021; Lira-Loarca et al., 2022). Other studies have also worked on the assessment of the various components of vulnerability and risk for floods of different types in the area with multiple approaches, including indicator-based methodologies (Quagliolo et al., 2021; Re et al., 2023) and hydrological and hydraulic methods (Silvestro et al., 2016), emphasizing the importance of developing combined coastal-fluvial flooding assessments in the region (De Angeli et al., 2018).

Susceptibility is most commonly defined as the physical predisposition of a system to be negatively affected by a dangerous phenomenon and suffer its consequences due to its intrinsic characteristics (Cardona et al., 2012; Mussi et al., 2018; Bentivoglio et al., 2022). It follows from this definition that assessing flood susceptibility within a region coincides with the identification of areas characterised by topographical, land cover or geomorphological characteristics that are most determinant to the accumulation of water (sometimes called flood-conditioning factors), such as the proximity to channels and depressions in the terrain and the presence of impervious soils. Flood susceptibility assessments are rooted in the identification of the presence of a set of such physical characteristics within the reference area and in the characterisation of their relationship to flood occurrence; they are essential tools for climate risk management and can be carried out through a wide variety of methodologies spanning from multi-criteria to statistical and data-driven methods (Arabameri et al., 2019).

Methodologies in Machine Learning (ML) represent good candidates supporting the different phases of the flood risk management process (Hasan et al., 2023; Park and Lee, 2020; Bentivoglio et al., 2022). Their speed in effectively solving regression and classification tasks related to predicting flood extent and depth makes them suitable, particularly when rapid flood appraisals are needed or as surrogate models in any context where more traditional physically-based methodologies might not be suitable because of resource, time or expertise constraints. Examples of data-driven applications to identify susceptible areas are currently being proposed in literature either in parallel to or in substitution of different methodologies; though, most such applications focus on pluvial and fluvial flooding, and examples of flood susceptibility for coastal flooding are relatively scarcer.

Most flood susceptibility assessments proposed in the literature rely on observational datasets on the location of past floods to characterise the local relationship between flood location and flood conditioning factors (Tehrany et al., 2015; Costache, 2019; Costache et al., 2020). For coastal inundation caused by storm surge and storm conditions in general, this is often not feasible because of their relatively short duration and the resulting complications in obtaining records of the flood extent either from in situ surveys or remote sensing sources (Cohen et al., 2019; Re et al., 2024). Therefore, only utilising observational data might beget biased analyses if a spatially uneven distribution characterises flood records or prevents the analysis for data-scarce coastal regions (Fang et al., 2022; Luo et al., 2023). For these reasons, integrating observations and models has proven useful in studying complex coastal environments and compound risks (Cohen et al., 2019). In line with previous attempts presented in literature where data-driven methods have been utilised to reproduce other model-derived flood datasets for classification and regression tasks, this work aims to assess Liguria's susceptibility to compound fluvial and coastal flooding through a data-driven approach. Identifying areas susceptible to flooding is set up as a supervised binary classification task in which labels about the membership to the fluvial and coastal floodplain are assigned to every pixel in the study area, utilising the outputs of numerical flood modelling produced in the context of the EU Floods Directive (EU, 2007) as ground truth.

The objective is to test the efficacy of a relatively straightforward method to be used in a surrogate-like manner to reproduce the potential flood extent obtained with more complex methodologies rather than to obtain new information about flood susceptibility in Liguria specifically (Woznicki et al., 2019; Löwe et al., 2021). This represents a novelty in the research on identifying areas susceptible to floods. This study further contributes to the literature in the field by testing several combinations of models of different complexity with different levels of spatial aggregation, with the aims of better characterising the relationship between model complexity and the task at hand and of identifying the geographical characteristics that might be instrumental in the outcome of the study. To the best of the author's knowledge, at the moment of designing the research and writing this article, no similar approach has been previously utilised to identify areas susceptible to floods in the study region.

The remainder of this article is organised as follows. Section 2 starts by outlining the framework of the study and then moves on to a presentation of the data utilised in the analysis as predictors and ground truth and its processing. An in-depth description of the different ML models utilised for the classification task of interest at varying levels of spatial aggregation is presented in the final portion of the section. Section 3 presents the results of the analysis and discusses them within the context of previous related findings, delineates the scope of application of this approach and highlights its strengths and limitations. Conclusions of the study are presented in Section 4.

2 Materials and Methods

2.1 Modelling Matrix

Models of increasing complexity - a linear Support Vector Machine (SVM) classifier, a Random Forest (RF) classifier, and a U-Net convolutional neural network (CNN) (Ronneberger et al., 2015) - were developed for the same reference area to evaluate the trade-off between model complexity and performance in reproducing the maps

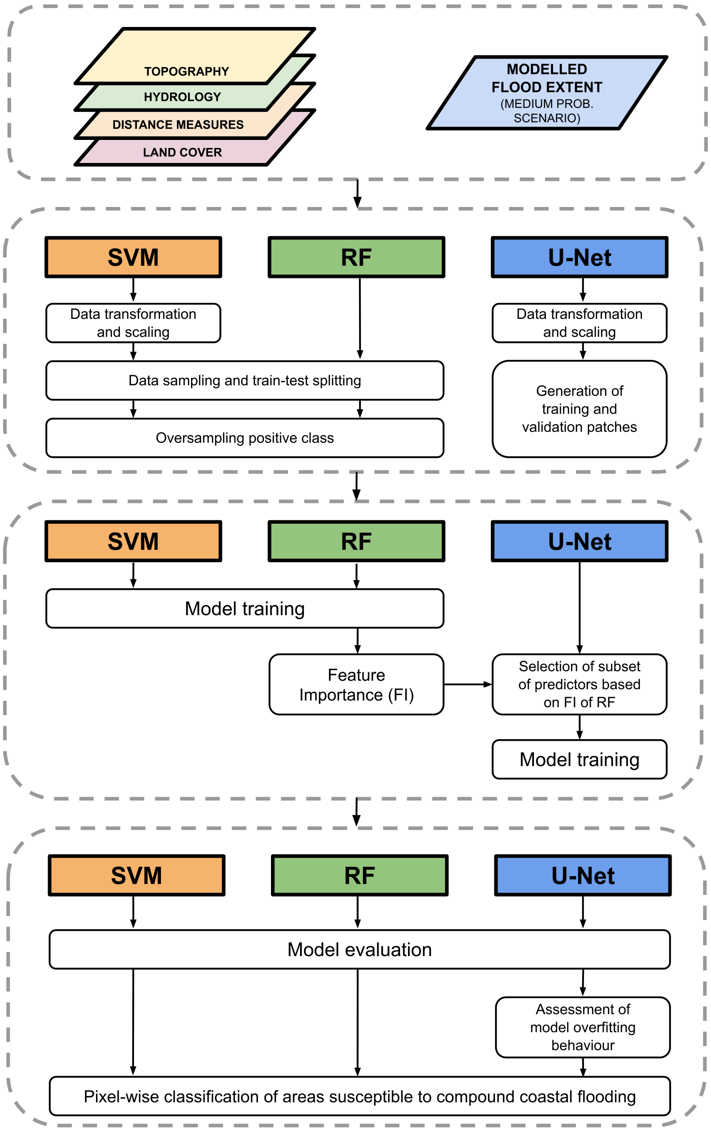

Fig. 1: Workflow scheme adopted in this study for the considered area.

of modelled flood extent utilised as ground truth following the workflow synthesised in Figure 1. The choice of these three specific models was driven by their increasing complexity and different approaches to spatial data handling. While SVM represents a baseline linear classifier, RF offers an intermediate complexity with built-in feature importance assessment. U-Net was selected for its proven capability in handling spatial dependencies in image segmentation tasks, although its application to flood susceptibility mapping remains relatively unexplored. RF had previously performed better than linear models in literature proposing analogous flood susceptibility assessments (Fang et al., 2022). Some examples of articles utilising more complex deep learning models for tasks similar to the one proposed here exist (specifically for floods in complex urban areas) (Zhao et al., 2020; Lei et al., 2021; Kalantar et al., 2021), but using image segmentation with fully convolutional networks to distinguish susceptible areas from non-susceptible areas within a region represents a relatively new approach.

The SVM and RF models were also developed at two different levels of spatial aggregation: one model for the whole region and individual models for each of the area's watersheds (Table 1). This spatial breakdown aimed to evaluate whether working with local models could lead to a better understanding of the variable influence of site-specific flood-inducing factors on flood susceptibility in different watersheds within the study area.

Unlike the simpler models in this study, U-Net uses a two-dimensional data structure. Because CNNs need a large number of images to train, this model was run only for the whole study area and not individual watersheds.

Table 1: Matrix of model types and levels of spatial aggregation adopted in the study.

	Increasing Model Complexity		
Increasing level of spatial breakdown	Linear SVM classifier for the whole study area	RF classifier for the whole study area	Image segmentation with U-Net
	Linear SVM classifier for individual UoAs	RF classifier for individual UoAs	N.A.

2.2 Level of Spatial Aggregation

The Unit of Analysis (hereafter, UoA) represents the smallest level of spatial aggregation considered in this study. UoAs are based on the reference areas (*Ambiti di Bacino* and relative sub-units) utilised by the regional government in the context of local watershed management plans (R. Liguria, 2016). Even though the UoAs are administrative in purpose, they are based on the location of watersheds and either completely overlap with them in the case of the larger ones or coincide with groups of small watersheds, especially in proximity to the coastline (see Figure 2). Utilising UoAs was considered a good compromise between the adherence to real-world hydrological and hydraulic processes and the constraints of available resources (Woznicki et al., 2019). Because of the focus on flooding in coastal areas, only watersheds draining towards the Ligurian Sea within the region were considered (R. Liguria).

The 61 regional UoAs are very heterogeneous in terms of size and the proportion of their area classified as flood prone according to the ground truth used in this study. Four of the 61 original UoAs were excluded from developing individual models since their limited size led to insufficient training instances. The whole study

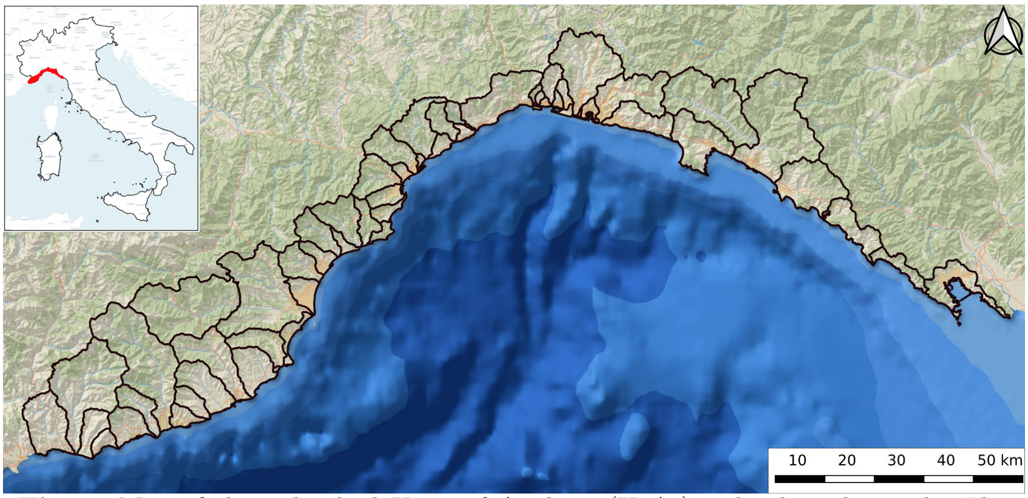

Fig. 2: Map of the individual Units of Analysis (UoAs) utilised in the study. The location of the study area is highlighted in red in the top left panel of the image. Basemap: ESRI Ocean.

region was defined as the aggregate of all the UoAs, including those excluded from the development of individual models.

2.3 Predictors and Ground Truth Data

This work is framed as a supervised learning task in which the outputs of numerical flood modelling produced in the context of the EU Floods Directive and integrated into the Italian regional planning through the *Piani di Gestione del Rischio di Alluvioni* (PGRA henceforth) are used as ground truth. Previous literature has shown that utilising such ground truth data in flood modelling should guarantee fewer missing inundations in the inventory and subsequently fewer negative sampling errors when compared to flood inundation maps obtained from observations (Fang et al., 2022; Luo et al., 2023; Woznicki et al., 2019; Löwe et al., 2021).

In coastal areas, the PGRA pluvial/fluvial component and the sea-driven component are usually modelled independently, and a simple overlay approach is utilised to consider the two drivers of flooding in conjunction. For the pluvial and fluvial flooding components, the PGRA map is the result of the aggregation of local appraisals carried out with diverse methodologies - from simple planar projections of the excess flow of water in channels corresponding to different return times (RTs) to more complex hydrological/hydraulic simulations. The coastal flood component is instead obtained as a simple planar projection of the total water level at the coastline computed with the MIKE21 model throughout the regional coastline, without explicitly modelling the overland flow (Warren and Bach, 1992; AdB App. Sett., 2021).

The area potentially flooded for a medium probability flooding event was considered, which corresponds to RTs of 100 years for the coastal flood component and 200 years for the pluvial/fluvial component (AdB App. Sett., 2021). Since several of Liguria's narrow rivers have a stream-like, intermittent character, areas categorised as rivers in local maps might be dry land for most of the year, making masking permanent water challenging, especially at the spatial resolution utilised in this study. Following a similar rationale, PGRA flood maps do not distinguish between permanent water and additional flood extent. It was therefore considered that masking permanent water would have removed too significant a portion of dry land susceptible to flooding in proximity to stream beds, and a decision was made only to mask the sea surface. This assumption might not hold if the study is performed at a more detailed spatial resolution.

Seventeen static predictors, mainly about the local topography, geomorphology and land cover, were employed in this study (see Table 2). The selection of predictors was based on their physical relevance to flood processes: topographic predictors capture terrain characteristics affecting water accumulation, hydrological indices represent water accumulation potential, distance metrics quantify proximity to water bodies, and spectral indices proxy for land cover and surface permeability. The relative importance of these predictors varies between coastal and inland areas, which may affect model performance depending on the local context.

Sinks in the regional Digital Elevation Model (DEM) were filled (Wang and Liu, 2006) before any further processing (Wu et al., 2019). The DEM was then used as the base to compute slope, aspect, profile curvature, tangential curvature, Overland Flow Distance from Channel Network (OFD), Horizontal Overland Flow Distance from channel Network (HOFD), Vertical Overland Flow Distance from Channel Network (VOFD), Vertical Distance to Channel Network (VDC), Topographic Wetness Index (TWI), Topographic Position Index (TPI) utilising the QGIS (QGIS.org, 2023) plugins for GRASS and SAGA GIS (Conrad et al., 2015).

The slope is widely considered among the most relevant predictors for identifying areas susceptible to floods because of its strong influence on runoff volume and velocity (Dodangeh et al., 2020; Costache et al., 2020). Regarding coastal flooding, the slope of the coast also determines the likelihood of it being interested in overtopping and ensuing inundation. Aspect (i.e., the direction of the downhill slope) is sometimes included among the predictors of (pluvial) flood susceptibility, as differential solar irradiance can influence the soil water content. The aspect was computed as a continuous angle from the DEM and then reclassified into eight classes of 45 degrees each. Curvature is commonly included among predictors of flood susceptibility (e.g. Tehrany et al. (2014); Wang et al. (2020); Mojaddadi et al. (2017)) as a proxy for the presence of dips in the terrain, which is more likely to fill up with water during flood events. Both profile and tangential curvature were considered in this study.

Various Topographic Wetness Indices (TWI) are utilised in literature to approximate the topographic contribution to surface runoff and hydrology (Wu et al., 2016). These indices are usually estimated based on the ratio between the upslope contributing area per unit contour length and the catchment slope (Beven and Kirby, 1979; Sørensen et al., 2006). This study utilised the index implementation proposed by Böhner et al. (2002).

The Topographic Position Index (TPI) identifies *the relative position of an area along a topographic gradient* (Guisan et al., 1999), thus indicating the likelihood of cells within the area of holding more (valleys) or less (slopes) water during flood events.

Measures of the distance to the channel network are among the most critical predictors of flood susceptibility and have been widely used in similar studies, especially about the pluvial and fluvial components of compound flooding (e.g. Woznicki et al. (2019); Chapi et al. (2017); Chen et al. (2020); Dodangeh et al. (2020)). The Overland Flow Distance (OFD) to the channel network represents the *distance to the nearest channel considering horizontal and vertical travel along the flow path* (Woznicki et al., 2019). The HOFD and VOFD represent, respectively, its horizontal and vertical components. The Vertical Distance to the channel (VDC) indicates the elevation distance between a location/pixel in the area and the nearest channel without considering the flow path. The measure of the distance of pixels from the coastline was included as a separate predictor in the analysis to better identify the coastal component of compound flooding.

Data on land cover (hereafter referred to as Land Use Land Cover, LULC) was retrieved from the CORINE Land Cover data product as a proxy for soil permeability and runoff reduction potential, reclassifying the original data into seven classes. Data pertaining to the origin of soils ('lithology' predictor) was included under the assumption that soils deposited during past floods would still be located in areas more prone to flooding in the present and future (Woznicki et al., 2019). For this reason, a regional dataset on lithology was retrieved and reclassified to identify soils of alluvial origin and soils from marine depositions along the coastline. More details on data reclassification are available in the supplementary material.

The Normalized Difference Vegetation Index (NDVI), the Normalized Difference Built-up Index (NDBI) and the Normalized Difference Water Index (NDWI) were included to serve as a proxy of - respectively - soil permeability (Chapi et al., 2017; Marco et al., 2022), soil sealing in urbanised areas and the presence of permanent water.

The complete list of predictors was utilised for the SVM and RF models. At the same time, the U-Net was run on a subset of the most relevant predictors chosen based on RF feature importance (see Section 3) to reduce problem complexity. Data was retrieved and processed as specified in Table 2. For the SVM and RF models, the data was then converted into a data frame consisting of one row per 15 m x 15 m pixel in the study area map, indexed by latitude and longitude. For the U-Net model, data was handled in simple numpy arrays (see Section 2.7). Additional feature engineering procedures (scaling, transformation and one-hot encoding) were performed for the SVM and U-Net models (Géron, 2023; Pedregosa et al., 2011).

2.4 Addressing Imbalanced Classification

In the binary classification task developed for this study, the positive class (i.e., pixels located in areas susceptible to flooding) constituted a low percentage of the total instances. The positive class amounted to roughly 2.1% of the total pixels for the whole study area. In the case of individual UoAs, this percentage varied between a

Table 2: Predictors and ground truth data utilised in the analysis.

Data	Original Source	Reference Year(s)	Data Type	Processing
DEM	Geoportale Liguria	2017	continuous	filled sinks according to Wang and Liu (2006)
Aspect	–	2017	categorical	computed from DEM according to Zevenbergen and Thorne (1987)
Profile curve.	–	2017	continuous	computed from DEM in GRASS/QGIS
Tangential curve.	–	2017	continuous	computed from DEM in GRASS/QGIS
OFD	–	2017	continuous	computed from DEM and channel network (O'Callaghan and Mark, 1984)
HOFD	–	2017	continuous	computed from DEM and channel network (O'Callaghan and Mark, 1984)
VOFD	–	2017	continuous	computed from DEM and channel network (O'Callaghan and Mark, 1984)
VDC	–	2017	continuous	computed from DEM and channel network
NDVI	Sentinel-2 L2A	2017-2019 (median comp.)	continuous	(NIR - Red)/(NIR + Red)
NDWI	Sentinel-2 L2A	2017-2019 (median comp.)	continuous	(Green - NIR)/(Green + NIR)
NDBI	Sentinel-2 L2A	2017-2019 (median comp.)	continuous	(SWIR - NIR)/(SWIR + NIR)
Distance from sea	–	2019	continuous	computed from DEM
TWI	–	2017	continuous	computed from DEM according to Böhner et al. (2002)
TPI	–	2017	continuous	computed from DEM according to Guisan et al. (1999)
LULC	Geoportale Liguria (vector 1:10000)	2019	categorical	CORINE Land Cover; reclassified in 7 classes and rasterized
Lithology	Geoportale Liguria (vector 1:50000)	2017	categorical	reclassified in 3 classes and rasterized
Flooding Risk (coastal + pluvial/fluvial)	AdB distr. dell'App. Settentrionale (vector 1:10000)	2021-2023	categorical	Medium prob. scenario selected for both types of flooding; union of vectors of the two components; binary raster generated from vector (1 = flooded; 0 = not flooded)

Note: All data was resampled from its original resolution to 15 m resolution.

minimum of 0.21% (excluding unsuitable UoAs) and a maximum of 10.77%, with the average around 2.5% and the median around 2%.

For the SVM and RF classification models, oversampling of the positive class was developed to account for class imbalance in the data. A randomly sampled subset of the pixels used in the study area was split into training and test sets with a 70-30 ratio (Tehrany et al., 2014; Dodangeh et al., 2020; Hasan et al., 2023). A second training dataset of equal dimension to the one obtained from the splitting procedure was obtained, forcing the positive class to represent 10% of the total training instances. For datasets about individual UoAs in which the positive class represented too little a percentage to allow positive oversampling at this level, the positive class was oversampled by drawing a maximum of 75% of the total positive instances present in the complete dataset (excluding test instances). In all circumstances, the test set was kept unmodified and was used later in the analysis to compare model performance between models trained on different training datasets.

The choice of oversampling ratio (10% positive class) represents a trade-off between avoiding excessive artificial data generation and preserving the natural rarity of flood-prone areas. The impact of alternative sampling ratios (20% and 50% positive class) was tested in the initial phases of the research. Still, it showed reduced overall performance (F1 score) due to the reduction in model precision.

The oversampling strategy described thus far was unsuitable for the U-Net model because of the two-dimensional data structure required by it. Therefore, the class imbalance was addressed as a rare object detection problem by choosing an appropriate loss function. The focal binary cross entropy loss function proposed by Lin et al. (2018) to address object detection tasks in cases of high foreground-background class imbalance in images was used for model training. It can be expressed as

$$FCE(p_t) = -\alpha(1 - p_t)^{\gamma} log(p_t), \tag{1}$$

with

$$p_t = \begin{cases} p & \text{if } \ y = 1 \\ (1 - p) & \text{otherwise} \end{cases} \tag{2}$$

where p is the model's estimated probability for the positive class. In Eq.1, α is a weight balancing factor for the positive class, and γ is a *focusing* parameter which adjusts the weight at which easy samples are down-weighted. α and γ were treated as hyperparameters to be optimised. The optimal α utilised ($\sim$0.98) corresponds to the training data's approximate percentage of negative values. The loss function was implemented in the U-Net model using TensorFlow's *BinaryFocalCrossentropy* loss class (Abadi et al., 2015).

2.5 Linear SVM Classifier

In this study, a linear SVM is the simplest model used to classify areas susceptible to floods. The SVM models were implemented with scikit-learn's SGDClassifier class utilising the hinge loss, corresponding to a soft-margin linear SVM (Pedregosa et al., 2011; Rosasco et al., 2004). Hyperparameter optimization was performed at the individual model level for the regularisation parameter, the number of iterations, the class

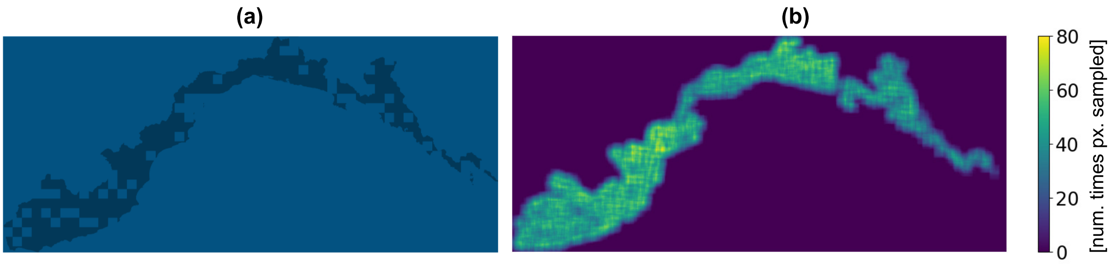

Fig. 3: The 57 validation **(a)** and 10000 training **(b)** patches used to train the U-Net model on the study area. For training patches, the colour bar represents the number of times each pixel was sampled to be included in a training patch.

weight and the learning rate. Optimised models were then fit to the two training datasets obtained as described in Section 2.4.

2.6 RF Classifier

RF models (Breiman, 2001) were chosen as the medium complexity model option and developed using scikit-learn's RandomForestClassifier class, which is based on the Classification and Regression Tree (CART) algorithm (Pedregosa et al., 2011). CART works by recursively splitting the training set into two subsets based on the values of a single feature and a threshold by selecting the feature-threshold pair that minimises a node impurity metric (entropy). Model hyperparameters for RF (number of trees in the forest, maximum depth of the tree, minimum samples for splitting, minimum samples in leaf) were optimised with cross-validation before full model deployment.

2.7 Segmentation of Areas Susceptible to Flooding with U-Net

The U-Net architecture is a Fully Convolutional Network (FCN) which was initially developed for image segmentation in the field of biomedical research by Ronneberger et al. (2015), and that has more recently found use in the natural hazards and flood research fields (Guo et al., 2022; Löwe et al., 2021). The research aim was framed to discern areas susceptible to flooding from the rest in much the same way as distinguishing an object from the background in a picture, whereby the map of the study areas is split into a series of images. Predictors fulfil the role of channels in the image, and model outputs represent the probability of each pixel in the image belonging to areas susceptible to flooding. The DEM, curvature, slope, TPI, TWI, VDC and VOFD were selected as predictors for the U-Net based on the results of RF feature importance (see supplementary material). A binary mask channel was also included to prevent the model from making predictions outside the study area.

The study area utilised for the U-Net model was composed only of UoAs directly connected to the sea to address compound flooding, even after removing some predictors relevant to the characterisation of marine-driven flooding utilised in simpler models. The resulting study area was then subdivided into a regular grid of patches of 256x256 pixels at the same 15 m resolution used for the SVM and RF models. Of these, 25% were selected for validation. 10000 randomly placed and partially overlapping training patches were sampled outside the validation areas (Figure 3).

Model and loss hyperparameters were optimised based on model performance as evaluated by average precision, recall and F1 score, preferring higher recall values to higher precision values. The distribution of the model predictions was also considered among the influential factors for choosing the best-performing model to address the imbalanced classification problem. The optimised U-Net had depth = 4, base filter size = 16, kernel size = 5 and utilised maximum pooling. The loss parameters α and γ were respectively $\sim$0.98 and 3. A rectified linear unit was chosen as activation. A dropout rate of 0.5 was applied at the end of every model layer. The U-Net model was developed in TensorFlow (version 2.16.1) with Keras (version 3.3.3) backend (Abadi et al., 2015; Chollet et al., 2015), adapted from the work of Löwe et al. (2021).

3 Results and Discussion

Model performance was evaluated using standard metrics for classification: precision (P), recall (R), and F1 score. For classification tasks such as this one, the evaluation of model performance depends on the objective of the analysis (Géron, 2023). Adopting a precautionary approach for flood risk reduction entails minimising false negatives and maximising model recall. For these reasons, higher recall values were preferred to higher precision whenever model performance was evaluated in this analysis. Table 3 shows precision, recall and F1 metrics for all models developed in this study.

Table 3: Performance metrics for all optimised models developed for this study. Results of SVM and RF are shown for individual UoAs (median values of the distribution) and the whole area considered. The U-Net model refers to the whole area considered.

	Precision	Recall	F1
SVM individual UoAs	0.65	0.70	0.66
SVM whole area	0.40	0.88	0.55
RF individual UoAs	0.81	0.84	0.82
RF whole area	0.46	0.89	0.61
U-Net whole area	0.04	0.74	0.06

In line with the aforementioned recall maximisation criterion, SVM and RF models trained on positively oversampled datasets performed better than those trained on randomly sampled datasets, showing better recall and F1 scores and worse precision. This is true both with regards to the whole study area (Figure 5) and more clearly at the individual UoAs level (Figure 6).

At both levels of spatial aggregation, RF outperformed SVM across all performance metrics considered. Nevertheless, it is acknowledged that SVM classifiers perform better for medium-sized datasets and that using it for the whole study region might have led to less than optimal performance (Géron, 2023). Visual inspection of a spatially complete map of the RF model prediction for a reference portion of the study area in

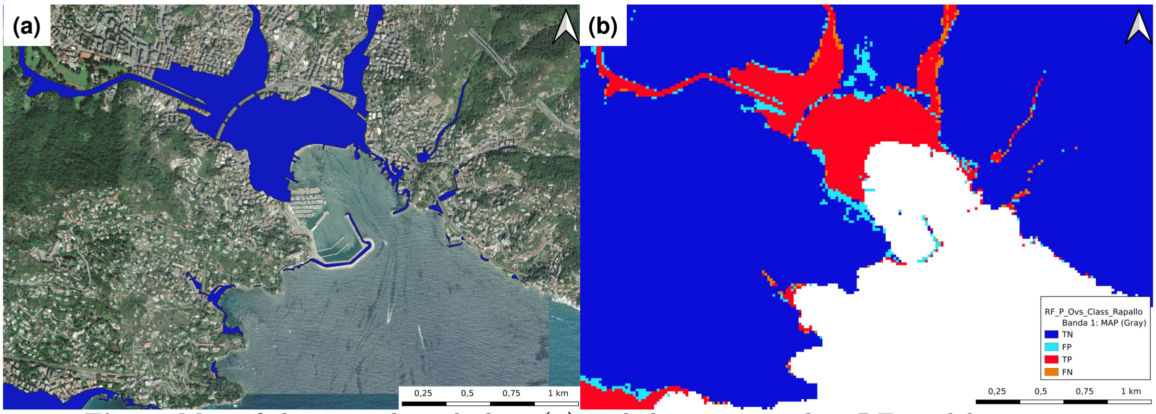

Fig. 4: Map of the ground truth data **(a)** and the corresponding RF model outputs **(b)**; example for the area of Rapallo/Santa Margherita Ligure. The model utilised to obtain this result is an RF model trained on a dataset with positive oversampling for the individual UoA. The model outputs have been categorised into the four classes of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN).

proximity of the Rapallo municipality (Figure 4) substantiates the good skill of the RF model in associating topographic characteristics to the membership to the coastal floodplain.

A limited number of predictors seemed to consistently significantly influence the model outcome in terms of feature importance (FI), even if some variation was observed. Elevation and the vertical distances to the channel network - most notably the VOFD - were relevant for all UoAs. Slope, TPI, TWI and lithology were also relevant predictors. The FI was used to discern which subset of predictors to utilise in the U-Net model. Though the lithology predictor was shown to be influential, its availability is more complex than that of most other topographic predictors used within the analysis. Therefore, in line with previous literature (Löwe et al., 2021; Guo et al., 2022), the U-Net was run with DEM-derived predictors only. The reader is referred to this article's supplementary material for more information on FI.

Despite its theoretical advantages in handling spatial data, the U-Net model showed unsatisfactory performance in discerning areas susceptible to compound flooding in the study area. Even though the optimised model showed sufficient recall values, model precision and F1 score were inferior (Table 3). The poor model skill can be ascribed to the model overfitting the training data and not being able to generalise to unseen instances, likely due to a complexity mismatch between the model architecture and the classification task (Géron, 2023). Alternative U-Net architectures were tested by reducing depth, exploring different filter sizes and reducing the number of predictors utilised in the model (Table 4). Namely, a U-Net model of the same structure as the one utilised before was run using the DEM, and the valid areas mask was used as the only predictors (input data in the shape 256x256x2). In a second attempt, VOFD was included among the predictors in addition to DEM and mask (input data in the shape 256x256x3). These two simplified versions of the U-Net model showed the same

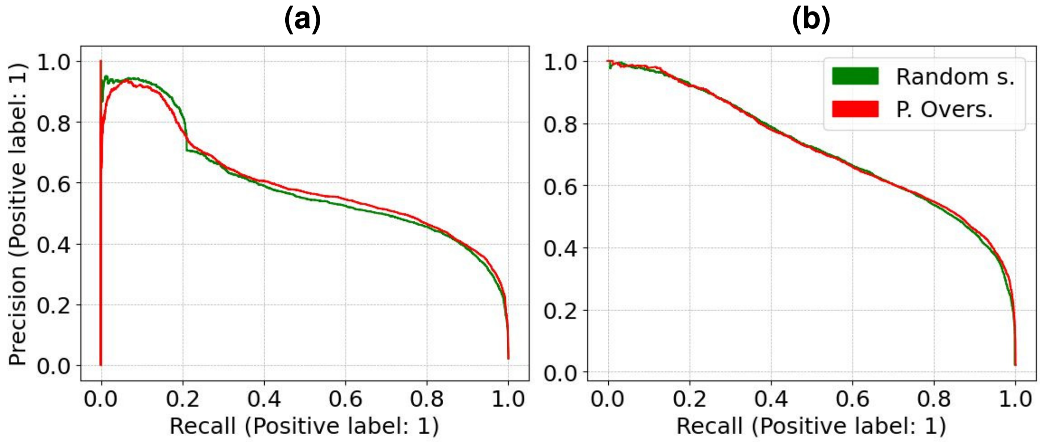

Fig. 5: Precision-recall curves for the linear SVM **(a)** and the RF **(b)** models trained on the whole area considered. The green line refers to the model trained on the randomly sampled dataset, while the red line refers to the model trained on the oversampled dataset.

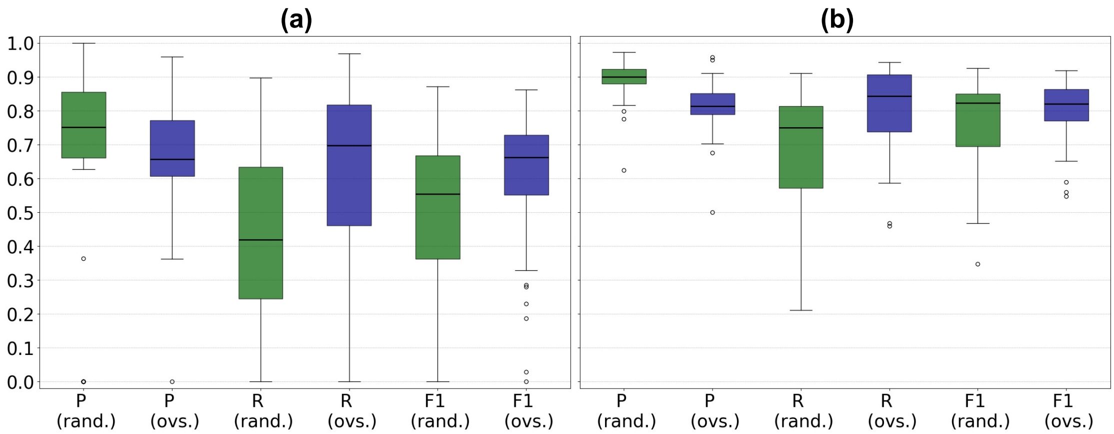

Fig. 6: Boxplots of model performance metrics (precision (P), recall (R) and F1 score (F1)) for linear SVM **(a)** and RF **(b)** models trained on randomly sampled datasets (green) and oversampled datasets (blue).

overfitting behaviour as before. On the other hand, RF models trained on the same predictors (Table 4) achieved better performance even when compared to the simpler U-Net models, suggesting that the limitation lies in the fundamental U-Net approach rather than specific architectural choices.

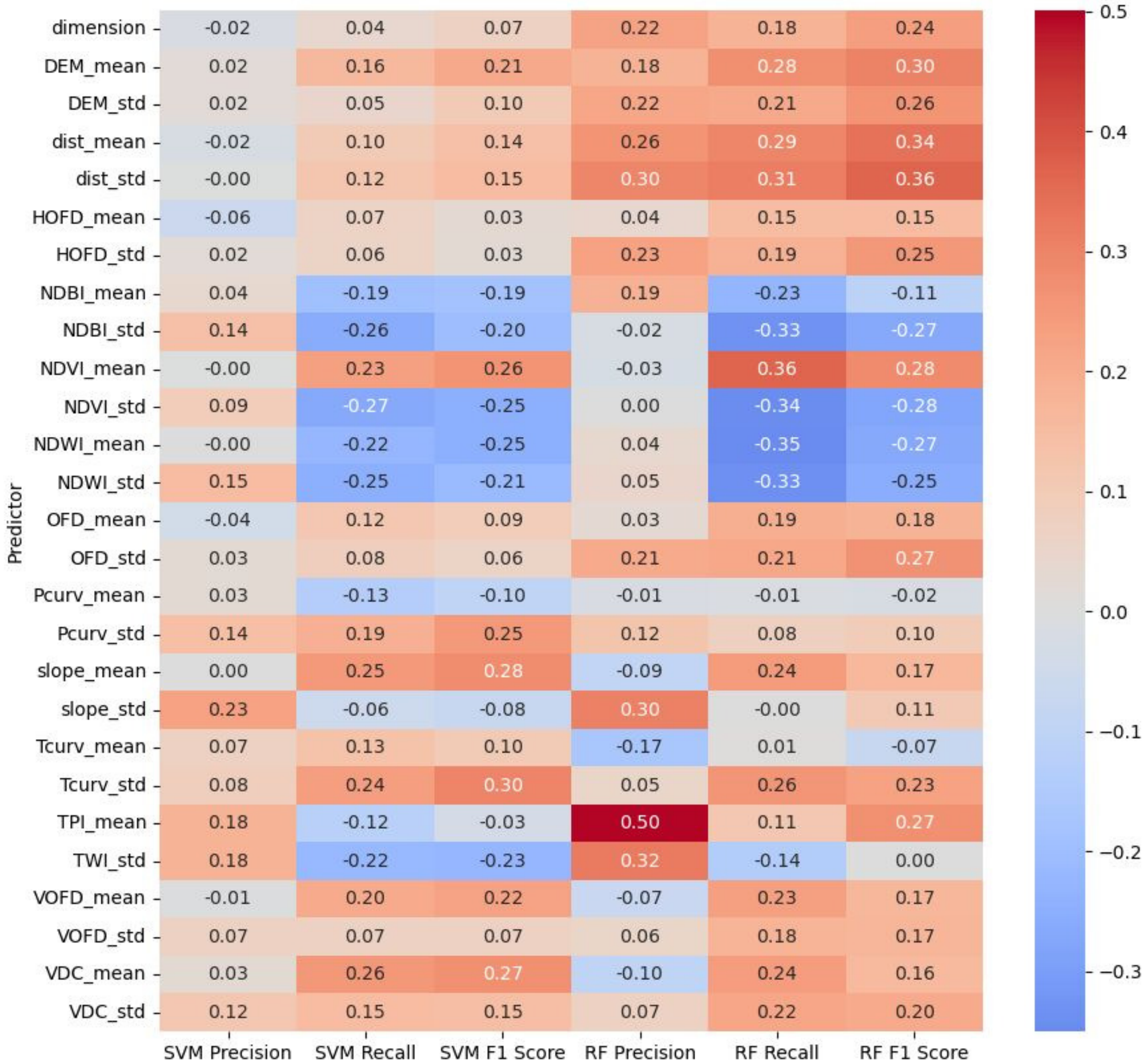

Fig. 7: Pearson's correlation coefficients between model performance metrics/UoA dimension and summary statistics of model predictors for models trained on individual UoAs. For categorical predictors, the correlation was analysed through Welch's ANOVA test between the predictor (median value in the UoA) and the continuous model performance metric; uncorrected p-values showed no significant correlation in all instances and are not reported here for clarity.

Table 4: Performance metrics for different configurations of predictors used in the U-Net model and comparison between RF and simpler U-Net models trained on DEM and DEM + VOFD only.

	Precision	Recall	F1
U-Net: all preds	0.04	0.74	0.06
U-Net: DEM (+ mask)	0.00	0.00	0.00
RF: DEM	0.31	0.66	0.42
U-Net: DEM and VOFD (+ mask)	0.04	0.64	0.06
RF: DEM and VOFD	0.36	0.84	0.50

3.1 Spatial Variability of SVM and RF Model Performance

Variability in performance among models trained on different UoAs was observed for both RF and SVM models (Figure 8). For the latter, some UoAs were characterised by poor model performance across all metrics considered. The correlation between model precision, recall and F1 score and summary statistics of predictors for each UoA was analysed (Figure 7) to gain more insight into the observed spatial variability. Even if it does not conform to an investigation of the causal relationship between local features and flood susceptibility, this analysis allowed us to gather geographically relevant information about the features of individual watersheds that might make a data-driven approach such as this more or less suitable to identify areas susceptible to flooding. The possible influence of the UoA dimension on model performance was also analysed, but it did not represent the strongest correlation with model performance compared to other predictors.

For both SVM and RF models, model precision was most strongly positively correlated with mean TPI, standard deviation of TWI and standard deviation of slope. The worst-performing SVM models were those referred to UoAs characterised by generally low mean slope, low standard deviation of TPI and low mean VDC (Figure 9). Furthermore, SVM model recalls were most strongly –positively– correlated with mean VDC and slope, and overall model performance (F1 score) had the strongest –positive– correlations with mean slope, mean VDC and standard deviation of TPI. These data highlight how SVM performed better for non-flat areas characterised by rough, elevated terrain in which channels are well-defined and represent a relatively small portion of the region.

When compared to SVM, RF models seemed to better learn spatial patterns linked to the natural presence of water, predicting more positive values than SVM in proximity to the coast and to channels, also leading to higher recall (Table 5).

RF model recall and F1 score were most strongly correlated with elevation and distance from the coastline. The positive correlation between RF model performance and standard deviation of distance from the coastline denotes that the identification of areas susceptible to compound fluvial and coastal floods tends to be easier for watersheds that extend in space transversely to the coastline, covering both areas where coastal flooding is likely to be the primary driver of susceptibility and more inland areas where fluvial flooding might be most relevant. For UoAs without significant

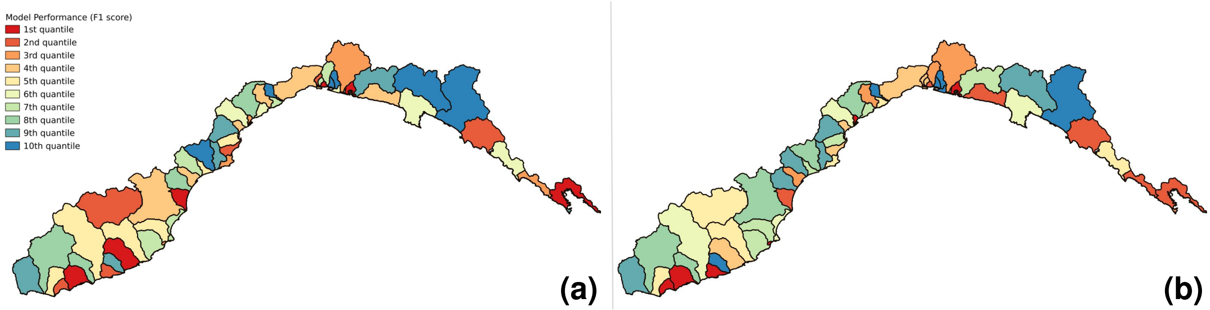

Fig. 8: Maps of F1 score for the different UoAs in the study region for linear SVM **(a)** and RF **(b)** models. Colours are based on the quantile of F1 score distribution.

inland extension, flood susceptibility might be mainly related to the coastal component of compound flooding; in these cases, the classification task might be made more challenging by homogeneous predictor distributions within the narrow coastal strip of land and by a particularly strong class imbalance.

The spatial heterogeneity in model performance can be attributed to the varying complexity of flood processes in different morphological settings and inconsistencies in data quality across the study area. The results of this study suggest that model selection should be terrain-specific, with simpler models (SVM) potentially being more appropriate for homogeneous coastal plains and more complex models (RF) better suited for heterogeneous terrain.

Table 5: Model performance metrics for SVM and RF models trained on the same UoA characterised by poor classification skill.

UoA ID	Precision	Recall	F1	Model
43	0.769231	0.171429	0.280374	Linear
43	0.796117	0.468571	0.589928	RF

3.2 Considerations on Model Performance

As is often the case for surrogates of physically based models, errors and simplifications intrinsic to the model being replicated are likely to be picked up by its data-driven approximations. In this case, the numerical models behind the ground truth used in this study were not homogeneous within the study area, and available metadata was sometimes insufficient to better characterise the assumptions behind the transformation of water level values into maps of the flooded area.

Recent literature focusing on compound flooding has cautioned against the issues that may arise from modelling different flood pathways separately without explicitly addressing their interrelations, both in terms of statistical dependence and from the point of view of the specific spatial patterns of compound flooding events (Green et al., 2024; Gao et al., 2023; Gori et al., 2020; Bilskie and Hagen, 2018; Mitu et al., 2023).

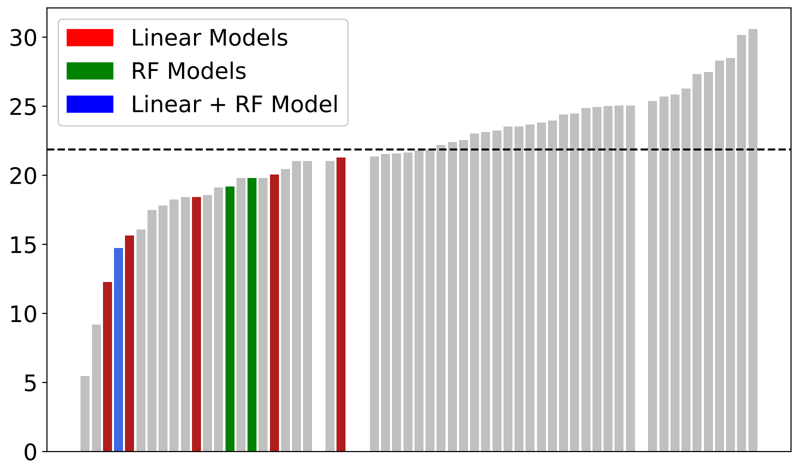

Fig. 9: Ordered bar plots of mean slope. The UoAs with poor performance in linear models are coloured in red, and those performing badly in RF models are coloured in green. The UoA 43 (poor performance for both linear and RF models) is blue. Barplots of standard deviation of TPI and mean VDC for the UoAs considered in this study show a similar clustering of UoAs with poor performance; the reader is referred to this article's supplementary material for additional plots

The approach presented in this study adopts a simplified definition of compound flooding as a simple overlay of the areas potentially susceptible to fluvial and marine-driven flooding. This approach can be helpful for first-order appraisals, provided it is acknowledged that interactions between different flood pathways can result in spatial patterns distinct from the straightforward sum of their maximum flood extent.

The need to tailor statistical approaches to the specific task and data in question each time without being able to know *a priori* which method will perform best is a well-known issue in statistical theory (Wolpert and Macready, 1997; James et al., 2023; Géron, 2023). Research has comprehensively addressed the model design problem (Hu et al., 2021), highlighting how choosing models exclusively on fit to observed data can lead to overfitting and poor ability to generalise (Myung, 2000). The U-Net model developed in this study was discarded because it overfits the data. Previous research showed how deep learning models can be used successfully for flood hazard analysis (Löwe et al., 2021; Guo et al., 2022). In future research developments, it might be worth investigating whether a more complex susceptibility classification task might be addressed with deep learning by focusing exclusively on the most low-lying portions of this coastal area and utilising as ground truth outputs of more precise numerical models.

In keeping with the renowned intricacies of studying water dynamics and resulting flood patterns in complex terrain such as low-lying coastal areas (Gallien et al., 2018), good model performance was more often associated with watersheds characterised by rougher and more elevated terrain. Therefore, SVM and RF performed well on average in this specific study area, likely because it represents an unusual example of a topographically complex coastal region, and the generalisability of the approach and findings of this study to coastal areas of different topographic conformations should be approached with caution.

3.3 Practical Implications for Risk Management

The results of this analysis have several practical implications for flood risk management in coastal regions. The demonstrated effectiveness of the RF model, particularly at the individual watershed level (F1 score 0.82), suggests its potential as a rapid screening tool for flood risk assessment.

This could be particularly valuable for Early Warning Systems in terms of rapid identification of potentially flood-prone areas during extreme weather events, priority setting for emergency response planning and support for real-time decision-making during compound flood events. This approach might also be applied fruitfully within an urban planning outlook by supporting preliminary assessments of flood susceptibility for new development areas, contributing to identifying critical zones requiring detailed hydrological studies, and supporting climate adaptation planning in coastal municipalities. Finally, it might guide decisions on resource allocation by contributing to the optimisation of monitoring network design, the prioritisation of areas for detailed numerical modelling and to the cost-effective planning of flood protection measures.

As previously mentioned (see Section 3.1), the performance comparison across different geographical settings reveals that model selection should be terrain-specific, with RF models being particularly effective in complex topography. In contrast, simpler SVM models might suffice for initial screening in coastal plains (Table 6). This understanding can guide the implementation of these methods in similar coastal regions, potentially reducing computational overhead while maintaining acceptable accuracy levels. These findings suggest that a tiered approach to flood susceptibility assessment might be most effective, where simple SVM models are used for initial rapid screening, RF models are applied in areas identified as potentially critical and detailed numerical modelling is reserved for high-risk zones requiring precise delineation. This hierarchical approach could significantly optimize resource allocation in flood risk management while maintaining robust risk assessment standards.

Table 6: Comparative model performance under different geographical conditions.

Geographical Setting	Model	Key Advantages	Limitations
Complex terrain	RF	Good pattern recognition	Computationally more demanding
	SVM	Simple implementation	Lower accuracy in complex terrain patterns
Coastal Plains	RF	Good detection of flood-prone areas	Less reliable in flat terrain
	SVM	Fast computation	Limited feature interaction capture

4 Conclusions

This study proposed a data-driven approach to identifying areas susceptible to compound fluvial and coastal flooding using outputs of numerical flood modelling as ground truth and data primarily related to regional topography as static predictors. The study area is the coastal region of Liguria, whose steep topographic conformation requires the joint analysis of surface flooding caused by precipitation filling torrential watercourses and marine-driven inundation. Building on previous related research, a comprehensive modelling approach was developed, in which models of varying complexity were run at different levels of spatial aggregation. This multifaceted approach contributes to the literature on flood susceptibility by providing new insights into the methodological pertinence and the physical characteristics of the local geography, which might influence the approach's success.

A subset of predictors seemed to be consistently relevant in defining susceptibility to flooding across all areas considered, and the variation in performance of SVM and RF models trained on individual watersheds within the study region hints at the relevance of local characteristics in determining the effectiveness of this approach. The identification of areas susceptible to flooding was overall satisfactory yet less reliable for watersheds characterised by generally flat terrain and located just up against the sea without much reach inland, which might be interpreted as the models mostly learning to identify the pluvial and fluvial components of flooding in the study area (Mobley et al., 2021).

Among the models tested in this study, the medium complexity RF model proved to be most skilful in the identification of areas susceptible to flooding in the study region, attaining performance comparable to similar studies published in literature both when trained on the whole study area and when developed for individual watersheds present in the region (Woznicki et al., 2019). Though the simpler linear SVM models tested also achieved satisfactory performance, their classification skill was more strongly affected by the class imbalance in the dataset, predicting membership to areas susceptible to flooding less often when compared to RF. The U-Net CNN tested in this study proved too complex for the classification task, resulting in generalised overfitting across the board of the different configurations tried.

Despite its limitations, this study demonstrated that a relatively straightforward data-driven approach can be effectively used in a surrogate-like fashion for the comprehensive identification of areas susceptible to compound flooding in coastal areas with similar topography to the one considered in this study. Using spatially complete modelled ground truth allowed to build from and improve on previous related research by introducing less spatial bias, verifying the results obtained for all the study regions considered and decoupling the susceptibility assessment from the necessity of extensive observational records on previous hazardous events in the area. At the same time, this approach allows flexibility for the integration of numerical models at varying levels of complexity based on local resources and data availability.

These methodological changes, in turn, shift the conception of data-driven susceptibility assessments from means that use records of localised flood events to generate new spatially complete information towards the use of machine learning as surrogate models aimed at approximating the outputs of more complex methodologies and thus identifying areas susceptible to floods with higher levels of reliability.

While this study demonstrates the potential of machine learning for flood susceptibility mapping, several key limitations should be considered for future applications. Firstly, the binary classification approach simplifies the complex nature of flood processes, and the static nature of the assessment fails to capture the temporal dynamics of flooding. Furthermore, the approach may not be directly transferable to regions with different morphological characteristics, which might require testing the approach in different geographical settings in future research developments. Future work should also focus on incorporating temporal predictors and developing hybrid approaches that combine data-driven and physical models. Finally, the approach might also be expanded from a simple classification approach to a regression task for flood depth prediction.

Nevertheless, to the best of the authors' knowledge, this study represents the first attempt of its kind for this Italian region. Furthermore, the proposed methodology can still find broad applicability as it constitutes a reliable topographic filter capable of first-order identification of areas susceptible to flooding with very low computational overhead, and it can be developed using widely available data. As such, maps of flood susceptibility obtained through this approach can provide relevant spatially explicit information in a straightforward and timely manner, which can then be used to complement data on exposure, hazard and adaptive capacity in the context of integrated vulnerability or risk assessments useful for local flood risk management purposes.

Supplementary information. This article has accompanying supplementary information, which can be found at https://doi.org/10.5281/zenodo.14599309

Statements and Declarations

Funding Lorenzo Minola is funded by the International Postdoc grant from the Swedish Research Council (2021-00444).
Competing interests The authors have no relevant financial or non-financial interests to disclose.
Author contributions All authors contributed to the study conception and design. Alice Re performed material preparation, data collection, and analysis. Alice Re wrote the first draft of the manuscript, and all authors commented on previous versions. All authors read and approved the final manuscript.

References

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G.S., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., Irving, G., Isard, M., Jia, Y., Jozefowicz, R., Kaiser, L., Kudlur, M., Levenberg, J., Mané, D., Monga, R., Moore, S., Murray, D., Olah, C., Schuster, M., Shlens, J., Steiner, B., Sutskever, I., Talwar, K., Tucker, P., Vanhoucke, V., Vasudevan, V., Viégas, F., Vinyals, O., Warden, P., Wattenberg, M., Wicke, M., Yu, Y., Zheng, X.: TensorFlow:

Large-Scale Machine Learning on Heterogeneous Systems. Software available from tensorflow.org (2015). https://www.tensorflow.org/

Sportello Cartografico. Ambiti di Bacino SC 1:25000 - ED. 1997. https://geoportal.regione.liguria.it. Accessed: 27/02/2024

Arabameri, A., Rezaei, K., Cerdà, A., Conoscenti, C., Kalantari, Z.: A comparison of statistical methods and multi-criteria decision making to map flood hazard susceptibility in northern iran. Science of The Total Environment **660**, 443–458 (2019) https://doi.org/10.1016/j.scitotenv.2019.01.021

Brandolini, P., Cevasco, A., Firpo, M., Robbiano, A., Sacchini, A.: Geo-hydrological risk management for civil protection purposes in the urban area of genoa (liguria, nw italy). Natural Hazards and Earth System Sciences **12**(4), 943–959 (2012) https://doi.org/10.5194/nhess-12-943-2012

Bevacqua, E., De Michele, C., Manning, C., Couasnon, A., Ribeiro, A.F.S., Ramos, A.M., Vignotto, E., Bastos, A., Blesić, S., Durante, F., Hillier, J., Oliveira, S.C., Pinto, J.G., Ragno, E., Rivoire, P., Saunders, K., Wiel, K., Wu, W., Zhang, T., Zscheischler, J.: Guidelines for studying diverse types of compound weather and climate events. Earth's Future **9**(11), 2021–002340 (2021) https://doi.org/10.1029/2021EF002340 https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2021EF002340

Bilskie, M.V., Hagen, S.C.: Defining flood zone transitions in low-gradient coastal regions. Geophysical Research Letters **45**(6), 2761–2770 (2018) https://doi.org/10.1002/2018GL077524

Bentivoglio, R., Isufi, E., Jonkman, S.N., Taormina, R.: Deep learning methods for flood mapping: a review of existing applications and future research directions. Hydrology and Earth System Sciences **26**(16), 4345–4378 (2022) https://doi.org/10.5194/hess-26-4345-2022

Beven, K.J., Kirby, M.J.: A physically based, variable contributing area model of basin hydrology / un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant. Hydrological Sciences Bulletin **24**(1), 43–69 (1979) https://doi.org/10.1080/02626667909491834

Böhner, J., Koethe, R., Conrad, O., Gross, J., Ringeler, A., Selige, T.: Soil regionalisation by means of terrain analysis and process parameterisation. Soil Classification 2001, 213–222 (2002)

Bevacqua, E., Maraun, D., Hobæk Haff, I., Widmann, M., Vrac, M.: Multivariate statistical modelling of compound events via pair-copula constructions: Analysis of floods in ravenna (italy). Hydrology and Earth System Sciences **21**(6), 2701–2723 (2017) https://doi.org/10.5194/hess-21-2701-2017

Bouwer, L.M.: Have disaster losses increased due to anthropogenic climate change? Bulletin of the American Meteorological Society **92**(1), 39–46 (2011) https://doi.org/10.1175/2010BAMS3092.1

Breiman, L.: Random forests. Machine Learning **45**(1), 5–32 (2001) https://doi.org/10.1023/A:1010933404324

Brandolini, P., Terranova, R.: Effects of the september, 1992 flood in the areas of genoa and savona (liguria, northern italy). Il Quaternario **7**, 473–478 (1994)

Chollet, F., et al.: Keras. https://keras.io (2015)

Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., Wehberg, J., Wichmann, V., Böhner, J.: System for automated geoscientific analyses (saga) v. 2.1.4. Geoscientific Model Development **8**(7), 1991–2007 (2015) https://doi.org/10.5194/gmd-8-1991-2015

Colangeli, C., Baldoni, A., Melito, L., Corvaro, S., Brocchini, M.: Harbour hydro-morphodynamics and freshwater discharges: The la spezia arsenale case. Water **15**(16) (2023) https://doi.org/10.3390/w15162865

Cramer, W., Guiot, K. J.and Marini: MedECC (2020) Climate and Environmental Change in the Mediterranean Basin – Current Situation and Risks for the Future. First Mediterranean Assessment Report. Union for the Mediterranean, Plan Bleu, UNEP/MAP, Marseille, France (2020). https://doi.org/10.5281/zenodo.4768833

Cramer, W., Guiot, J., Fader, M., Garrabou, J., Gattuso, J.-P., Iglesias, A., Lange, M.A., Lionello, P., Llasat, M.C., Paz, S., Peñuelas, J., Snoussi, M., Toreti, A., Tsimplis, M.N., Xoplaki, E.: Climate change and interconnected risks to sustainable development in the mediterranean. Nature Climate Change **8**(11), 972–980 (2018) https://doi.org/10.1038/s41558-018-0299-2

Chen, W., Li, Y., Xue, W., Shahabi, H., Li, S., Hong, H., Wang, X., Bian, H., Zhang, S., Pradhan, B., Ahmad, B.B.: Modeling flood susceptibility using data-driven approaches of naïve bayes tree, alternating decision tree, and random forest methods. Science of The Total Environment **701**, 134979 (2020) https://doi.org/10.1016/j.scitotenv.2019.134979

Costache, R.: Flash-flood potential index mapping using weights of evidence, decision trees models and their novel hybrid integration. Stochastic Environmental Research and Risk Assessment **33**(7), 1375–1402 (2019) https://doi.org/10.1007/s00477-019-01689-9

Costache, R., Pham, Q.B., Avand, M., Thuy Linh, N.T., Vojtek, M., Vojteková, J., Lee, S., Khoi, D.N., Thao Nhi, P.T., Dung, T.D.: Novel hybrid models between bivariate statistics, artificial neural networks and boosting algorithms for flood susceptibility assessment. Journal of Environmental Management **265**, 110485 (2020) https://doi.org/10.1016/j.jenvman.2020.110485

Costache, R., Pham, Q.B., Sharifi, E., Linh, N.T.T., Abba, S.I., Vojtek, M., Vojteková, J., Nhi, P.T.T., Khoi, D.N.: Flash-flood susceptibility assessment using multi-criteria decision making and machine learning supported by remote sensing and gis techniques. Remote Sensing **12**(1) (2020) https://doi.org/10.3390/rs12010106

Cohen, S., Raney, A., Munasinghe, D., Loftis, J.D., Molthan, A., Bell, J., Rogers, L., Galantowicz, J., Brakenridge, G.R., Kettner, A.J., Huang, Y.-F., Tsang, Y.-P.: The floodwater depth estimation tool (fwdet v2.0) for improved remote sensing analysis of coastal flooding. Natural Hazards and Earth System Sciences **19**(9), 2053–2065 (2019) https://doi.org/10.5194/nhess-19-2053-2019

Chapi, K., Singh, V.P., Shirzadi, A., Shahabi, H., Bui, D.T., Pham, B.T., Khosravi, K.: A novel hybrid artificial intelligence approach for flood susceptibility assessment. Environmental Modelling & Software **95**, 229–245 (2017) https://doi.org/10.1016/j.envsoft.2017.06.012

Cardona, O.D., Aalst, M.K., Birkmann, M., Fordham, G., McGregor, G., Perez, R., Pulwarty, R.S., Schipper, E.L.F., Sinh, B.T.: Determinants of risk: exposure and vulnerability. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 65-108 (2012)

Déguénon, S.D.D.M., Adade, R., Teka, O., Aheto, D.W., Sinsin, B.: Sea-level rise and flood mapping: a review of models for coastal management. Natural Hazards **120**(3), 2155–2178 (2024) https://doi.org/10.1007/s11069-023-06225-1

Dodangeh, E., Choubin, B., Eigdir, A.N., Nabipour, N., Panahi, M., Shamshirband, S., Mosavi, A.: Integrated machine learning methods with resampling algorithms for flood susceptibility prediction. Science of The Total Environment **705**, 135983 (2020) https://doi.org/10.1016/j.scitotenv.2019.135983

De Angeli, S., D'Andrea, M., Cazzola, G., Dolia, D., Duo, E., Rebora, N.: Coastal risk assessment framework: Comparison of modelled fluvial and marine inundation impacts, bocca di magra, ligurian coast, italy. Coastal Engineering **134**, 229–240 (2018) https://doi.org/10.1016/j.coastaleng.2017.09.011 . RISC-KIT: Resilience-increasing Strategies for Coasts – Toolkit

Eilander, D., Couasnon, A., Sperna Weiland, F.C., Ligtvoet, W., Bouwman, A., Winsemius, H.C., Ward, P.J.: Modeling compound flood risk and risk reduction using a globally applicable framework: a pilot in the sofala province of mozambique. Natural Hazards and Earth System Sciences **23**(6), 2251–2272 (2023) https://doi.org/10.5194/nhess-23-2251-2023

EU: Directive 2007/60/EC of the European Parliament and of the Council of 23 October 2007 on the assessment and management of flood risks. https://eur-lex.europa.

eu/eli/dir/2007/60/oj (2007)

Ferrando, I., Brandolini, P., Federici, B., Lucarelli, A., Sguerso, D., Morelli, D., Corradi, N.: Coastal modification in relation to sea storm effects: Application of 3d remote sensing survey in sanremo marina (liguria, nw italy). Water **13**(8) (2021) https://doi.org/10.3390/w13081040

Federici, B., Corradi, N., Ferrando, I., Sguerso, D., Lucarelli, A., Guida, S., Brandolini, P.: Remote sensing techniques applied to geomorphological mapping of rocky coast: the case study of gallinara island (western liguria, italy). European Journal of Remote Sensing **52**(sup4), 123–136 (2019) https://doi.org/10.1080/22797254.2019.1686957

Fang, L., Huang, J., Cai, J., Nitivattananon, V.: Hybrid approach for flood susceptibility assessment in a flood-prone mountainous catchment in china. Journal of Hydrology **612**, 128091 (2022) https://doi.org/10.1016/j.jhydrol.2022.128091

Garnier, E., Ciavola, P., Spencer, T., Ferreira, O., Armaroli, C., McIvor, A.: Historical analysis of storm events: Case studies in france, england, portugal and italy. Coastal Engineering **134**, 10–23 (2018) https://doi.org/10.1016/j.coastaleng.2017.06.014 . RISC-KIT: Resilience-increasing Strategies for Coasts – Toolkit

Gao, L., Du, H., Huang, H., Zhang, L., Zhang, P.: Modelling the compound floods upon combined rainfall and storm surge events in a low-lying coastal city. Journal of Hydrology **627**, 130476 (2023) https://doi.org/10.1016/j.jhydrol.2023.130476

Green, J., Haigh, I., Quinn, N., Neal, J., Wahl, T., Wood, M., Eilander, D., Ruiter, M., Ward, P., Camus, P.: Review article: A comprehensive review of compound flooding literature with a focus on coastal and estuarine regions. EGUsphere **2024**, 1–108 (2024) https://doi.org/10.5194/egusphere-2024-2247

Gallien, T.W., Kalligeris, N., Delisle, M.-P.C., Tang, B.-X., Lucey, J.T.D., Winters, M.A.: Coastal flood modeling challenges in defended urban backshores. Geosciences **8**(12) (2018) https://doi.org/10.3390/geosciences8120450

Gori, A., Lin, N., Xi, D.: Tropical cyclone compound flood hazard assessment: From investigating drivers to quantifying extreme water levels. Earth's Future **8**(12), 2020–001660 (2020) https://doi.org/10.1029/2020EF001660 https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2020EF001660

Guo, Z., Moosavi, V., Leitão, J.P.: Data-driven rapid flood prediction mapping with catchment generalizability. Journal of Hydrology **609**, 127726 (2022) https://doi.org/10.1016/j.jhydrol.2022.127726

Guarnieri, A., Saremi, S., Pedroncini, A., Jensen, J.H., Torretta, S., Vaccari, M., Vincenzi, C.: Effects of marine traffic on sediment erosion and accumulation in ports: a new model-based methodology. Ocean Science **17**(2), 411–430 (2021) https://doi.org/10.5194/os-17-411-2021

Guisan, A., Weiss, S.B., Weiss, A.D.: Glm versus cca spatial modeling of plant species distribution. Plant Ecology **143**(1), 107–122 (1999) https://doi.org/10.1023/A:1009841519580

Géron, A.: Hands-On Machine Learning With Scikit-Learn, Keras, and TensorFlow - Third Edition. O'Reilly Media, Inc., Seastopol, CA, USA (2023)

Hasan, M.H., Ahmed, A., Nafee, K.M., Hossen, M.A.: Use of machine learning algorithms to assess flood susceptibility in the coastal area of bangladesh. Ocean & Coastal Management **236**, 106503 (2023) https://doi.org/10.1016/j.ocecoaman.2023.106503

Hu, X., Chu, L., Pei, J., Liu, W., Bian, J.: Model complexity of deep learning: a survey. Knowledge and Information Systems **63**(10), 2585–2619 (2021) https://doi.org/10.1007/s10115-021-01605-0

Hinkel, J., Feyen, L., Hemer, M., Le Cozannet, G., Lincke, D., Marcos, M., Mentaschi, L., Merkens, J.L., Moel, H., Muis, S., Nicholls, R.J., Vafeidis, A.T., Wal, R.S.W., Vousdoukas, M.I., Wahl, T., Ward, P.J., Wolff, C.: Uncertainty and bias in global to regional scale assessments of current and future coastal flood risk. Earth's Future **9**(7) (2021) https://doi.org/10.1029/2020EF001882 https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2020EF001882

Hallegatte, S., Green, C., Nicholls, R.J., Corfee-Morlot, J.: Future flood losses in major coastal cities. Nature Climate Change **3**(9), 802–806 (2013) https://doi.org/10.1038/nclimate1979

Jongman, B., Ward, P.J., Aerts, J.C.J.H.: Global exposure to river and coastal flooding: Long term trends and changes. Global Environmental Change **22**(4), 823–835 (2012) https://doi.org/10.1016/j.gloenvcha.2012.07.004

James, G., Witten, D., Hastie, T., Tibshiranu, R., Taylor, J.: An Introduction to Statistical Learning with Applications in Python. Springer, ??? (2023). https://doi.org/10.1007/978-3-031-38747-0

Kalantar, B., Ueda, N., Saeidi, V., Janizadeh, S., Shabani, F., Ahmadi, K., Shabani, F.: Deep neural network utilizing remote sensing datasets for flood hazard susceptibility mapping in brisbane, australia. Remote Sensing **13**(13) (2021) https://doi.org/10.3390/rs13132638

Löwe, R., Böhm, J., Jensen, D.G., Leandro, J., Rasmussen, S.H.: U-flood – topographic deep learning for predicting urban pluvial flood water depth. Journal of Hydrology **603**, 126898 (2021) https://doi.org/10.1016/j.jhydrol.2021.126898

Lei, X., Chen, W., Panahi, M., Falah, F., Rahmati, O., Uuemaa, E., Kalantari, Z., Ferreira, C.S.S., Rezaie, F., Tiefenbacher, J.P., Lee, S., Bian, H.: Urban flood modeling using deep-learning approaches in seoul, south korea. Journal of Hydrology **601**, 126684 (2021) https://doi.org/10.1016/j.jhydrol.2021.126684

Lin, T.-Y., Goyal, P., Girshick, R., He, K., Dollár, P.: Focal Loss for Dense Object Detection (2018). https://arxiv.org/abs/1708.02002

Lira-Loarca, A., Cáceres-Euse, A., De-Leo, F., Besio, G.: Wave modeling with unstructured mesh for hindcast, forecast and wave hazard applications in the mediterranean sea. Applied Ocean Research **122**, 103118 (2022) https://doi.org/10.1016/j.apor.2022.103118

Luo, Z., Tian, J., Zeng, J., Pilla, F.: Resilient landscape pattern for reducing coastal flood susceptibility. Science of The Total Environment **856**, 159087 (2023) https://doi.org/10.1016/j.scitotenv.2022.159087

Mussi, C.S., Bonetti, J., Sperb, R.M.: Coastal sensitivity and population exposure to sea level rise: a case study on santa catarina island, brazil. Journal of Coastal Conservation **22**(6), 1117–1128 (2018) https://doi.org/10.1007/s11852-018-0619-8

Marco, Z., Elena, A., Anna, S., Silvia, T., Andrea, C.: Spatio-temporal cross-validation to predict pluvial flood events in the metropolitan city of venice. Journal of Hydrology **612**, 128150 (2022) https://doi.org/10.1016/j.jhydrol.2022.128150

Mojaddadi, H., Pradhan, B., Nampak, H., Ahmad, N., Ghazali, A.H.: Ensemble machine-learning-based geospatial approach for flood risk assessment using multi-sensor remote-sensing data and gis. Geomatics, Natural Hazards and Risk **8**(2), 1080–1102 (2017) https://doi.org/10.1080/19475705.2017.1294113

Mobley, W., Sebastian, A., Blessing, R., Highfield, W.E., Stearns, L., Brody, S.D.: Quantification of continuous flood hazard using random forest classification and flood insurance claims at large spatial scales: a pilot study in southeast texas. Natural Hazards and Earth System Sciences **21**(2), 807–822 (2021) https://doi.org/10.5194/nhess-21-807-2021

Mitu, M.F., Sofia, G., Shen, X., Anagnostou, E.N.: Assessing the compound flood risk in coastal areas: Framework formulation and demonstration. Journal of Hydrology **626**, 130278 (2023) https://doi.org/10.1016/j.jhydrol.2023.130278

Myung, I.J.: The importance of complexity in model selection. Journal of Mathematical Psychology **44**(1), 190–204 (2000) https://doi.org/10.1006/jmps.1999.1283

Nicholls, R.J., Cazenave, A.: Sea-level rise and its impact on coastal zones. Science **328**(5985), 1517–1520 (2010) https://doi.org/10.1126/science.1185782 https://www.science.org/doi/pdf/10.1126/science.1185782

Neumann, B., Vafeidis, A.T., Zimmermann, J., Nicholls, R.J.: Future coastal population growth and exposure to sea-level rise and coastal flooding - a global assessment. PLOS ONE **10**(3), 1–34 (2015) https://doi.org/10.1371/journal.pone.0118571

O'Callaghan, J.F., Mark, D.M.: The extraction of drainage networks from digital elevation data. Computer Vision, Graphics, and Image Processing **28**(3), 323–344 (1984) https://doi.org/10.1016/S0734-189X(84)80011-0

Oprandi, A., Mucerino, L., De Leo, F., Bianchi, C.N., Morri, C., Azzola, A., Benelli, F., Besio, G., Ferrari, M., Montefalcone, M.: Effects of a severe storm on seagrass meadows. Science of The Total Environment **748**, 141373 (2020) https://doi.org/10.1016/j.scitotenv.2020.141373

Piano di gestione Rischio Alluvioni - Distretto Appennino Settentrionale - Unit of Management: Bacino Regionale della Liguria. https://www.appenninosettentrionale.it/itc/?page_id=2019 (2016)

Autorità di Bacino Distrettuale dell'Appennino Settentrionale. Aggiornamento e Revisione del Piano di Gestione del Rischio di Alluvione - Secondo Ciclo di Gestione - relazione Metodologica. https://www.appenninosettentrionale.it/itc/?page_id=5262. Accessed: 19/02/2024 (2021)

Park, S.-J., Lee, D.-K.: Prediction of coastal flooding risk under climate change impacts in south korea using machine learning algorithms. Environmental Research Letters **15**(9), 094052 (2020) https://doi.org/10.1088/1748-9326/aba5b3

Pesci, A., Teza, G., Bisson, M., Muccini, F., Stefanelli, P., Anzidei, M., Carluccio, R., Nicolosi, I., Galvani, A., Sepe, V., Carmisciano, C.: Monitoring of a coastal zone by independent fast photogrammetric surveys: the case of monterosso a mare (ligurian sea, italy). Journal of Geosciences and Geomatics **4**(4), 73–81 (2016) https://doi.org/10.12691/jgg-4-4-1

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E.: Scikit-learn: Machine learning in Python. Journal of Machine Learning Research **12**, 2825–2830 (2011)

Quagliolo, C., Comino, E., Pezzoli, A.: Experimental flash floods assessment through urban flood risk mitigation (ufrm) model: The case study of ligurian coastal cities. Frontiers in Water **3** (2021) https://doi.org/10.3389/frwa.2021.663378

QGIS.org. QGIS Geographic Information System. http://qgis.org (2023)

Ronneberger, O., Fischer, P., Brox, T.: U-net: Convolutional networks for biomedical image segmentation. CoRR **abs/1505.04597** (2015) 1505.04597

Re, A., Minola, L., Pezzoli, A.: Climate scenarios for coastal flood vulnerability assessments: A case study for the ligurian coastal region. Climate **11**(3) (2023) https://doi.org/10.3390/cli11030056

Re, A., Minola, L., Pezzoli, A., Camps-Valls, G.: Predicting Coastal Flooding in the Mediterranean with Remote Sensing and Machine Learning. EGU General Assembly 2024, Vienna, Austria, 14–19 Apr 2024, EGU24-9306 (2024). https://doi.org/10.5194/egusphere-egu24-9306,2024

Rosasco, L., Vito, E.D., Caponnetto, A., Piana, M., Verri, A.: Are Loss Functions All the Same? Neural Computation **16**(5), 1063–1076 (2004) https://doi.org/10.1162/089976604773135104 https://direct.mit.edu/neco/article-pdf/16/5/1063/815882/089976604773135104.pdf

Syvitski, J.P.M., Kettner, A.J., Overeem, I., Hutton, E.W.H., Hannon, M.T., Brakenridge, G.R., Day, J., Vörösmarty, C., Saito, Y., Giosan, L., Nicholls, R.J.: Sinking deltas due to human activities. Nature Geoscience **2**(10), 681–686 (2009) https://doi.org/10.1038/ngeo629

Silvestro, F., Rebora, N., Rossi, L., Dolia, D., Gabellani, S., Pignone, F., Trasforini, E., Rudari, R., De Angeli, S., Masciulli, C.: What if the 25 october 2011 event that struck cinque terre (liguria) had happened in genoa, italy? flooding scenarios, hazard mapping and damage estimation. Natural Hazards and Earth System Sciences **16**(8), 1737–1753 (2016) https://doi.org/10.5194/nhess-16-1737-2016

Sarkar, N., Rizzo, A., Vandelli, V., Soldati, M.: A literature review of climate-related coastal risks in the mediterranean, a climate change hotspot. Sustainability **14**(23) (2022) https://doi.org/10.3390/su142315994

Sørensen, R., Zinko, U., Seibert, J.: On the calculation of the topographic wetness index: evaluation of different methods based on field observations. Hydrology and Earth System Sciences Discussions **10**(1), 101–112 (2006)

Tehrany, M.S., Pradhan, B., Jebur, M.N.: Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in gis. Journal of Hydrology **512**, 332–343 (2014) https://doi.org/10.1016/j.jhydrol.2014.03.008

Tehrany, M.S., Pradhan, B., Jebur, M.N.: Flood susceptibility analysis and its verification using a novel ensemble support vector machine and frequency ratio method. Stochastic Environmental Research and Risk Assessment **29**(4), 1149–1165 (2015) https://doi.org/10.1007/s00477-015-1021-9

Tebaldi, C., Ranasinghe, R., Vousdoukas, M., Rasmussen, D.J., Vega-Westhoff, B., Kirezci, E., Kopp, R.E., Sriver, R., Mentaschi, L.: Extreme sea levels at different global warming levels. Nature Climate Change **11**(9), 746–751 (2021) https://doi.org/10.1038/s41558-021-01127-1

Piani di Bacino Rilievo Regionale - Fasce Fluviali. https://srvcarto.regione.liguria.

it/geoviewer2/pages/apps/geoportale/index.html?id=447. referenced Layer: 'Situazione Informatizzazione'. Accessed: 27/02/2024

Vousdoukas, M.I., Mentaschi, L., Voukouvalas, E., Verlaan, M., Jevrejeva, S., Jackson, L.P., Feyen, L.: Global probabilistic projections of extreme sea levels show intensification of coastal flood hazard. Nature Communications **9**(3) (2018) https://doi.org/10.1038/s41467-018-04692-w

Vannucchi, V., Taddei, S., Capecchi, V., Bendoni, M., Brandini, C.: Dynamical downscaling of era5 data on the north-western mediterranean sea: From atmosphere to high-resolution coastal wave climate. Journal of Marine Science and Engineering **9**(2) (2021) https://doi.org/10.3390/jmse9020208

Warren, I.R., Bach, H.K.: Mike 21: a modelling system for estuaries, coastal waters and seas. Environmental Software **7**(4), 229–240 (1992) https://doi.org/10.1016/0266-9838(92)90006-P . 3rd International Software Exhibition for Environmental Science and Engineering

Woznicki, S.A., Baynes, J., Panlasigui, S., Mehaffey, M., Neale, A.: Development of a spatially complete floodplain map of the conterminous united states using random forest. Science of The Total Environment **647**, 942–953 (2019) https://doi.org/10.1016/j.scitotenv.2018.07.353

Wang, Y., Fang, Z., Hong, H., Peng, L.: Flood susceptibility mapping using convolutional neural network frameworks. Journal of Hydrology **582**, 124482 (2020) https://doi.org/10.1016/j.jhydrol.2019.124482

Wu, Y., Giri, S., Qiu, Z.: Understanding the spatial distribution of hydrologic sensitive areas in the landscape using soil topographic index approach. International Soil and Water Conservation Research **4**(4), 278–283 (2016) https://doi.org/10.1016/j.iswcr.2016.10.002

Wang, L., Liu, H.: An efficient method for identifying and filling surface depressions in digital elevation models for hydrologic analysis and modelling. International Journal of Geographical Information Science **20**(2), 193–213 (2006) https://doi.org/10.1080/13658810500433453

Wu, Q., Lane, C.R., Wang, L., Vanderhoof, M.K., Christensen, J.R., Liu, H.: Efficient delineation of nested depression hierarchy in digital elevation models for hydrological analysis using level-set method. JAWRA Journal of the American Water Resources Association **55**(2), 354–368 (2019) https://doi.org/10.1111/1752-1688.12689

Wolpert, D.H., Macready, W.G.: No free lunch theorems for optimization. IEEE Transactions on Evolutionary Computation **1**(1), 67–82 (1997) https://doi.org/10.1109/4235.585893

Wu, W., McInnes, K., O'Grady, J., Hoeke, R., Leonard, M., Westra, S.: Mapping dependence between extreme rainfall and storm surge. Journal of Geophysical Research: Oceans **123**(4), 2461–2474 (2018) https://doi.org/10.1002/2017JC013472 https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2017JC013472

Wu, W., Westra, S., Leonard, M.: Estimating the probability of compound floods in estuarine regions. Hydrology and Earth System Sciences **25**(5), 2821–2841 (2021) https://doi.org/10.5194/hess-25-2821-2021

Zhao, G., Pang, B., Xu, Z., Peng, D., Zuo, D.: Urban flood susceptibility assessment based on convolutional neural networks. Journal of Hydrology **590**, 125235 (2020) https://doi.org/10.1016/j.jhydrol.2020.125235

Zevenbergen, L.W., Thorne, C.R.: Quantitative analysis of land surface topography. Earth Surface Processes and Landforms **12**(1), 47–56 (1987) https://doi.org/10.1002/esp.3290120107 https://onlinelibrary.wiley.com/doi/pdf/10.1002/esp.3290120107