Università
Ca'Foscari
Venezia
Dipartimento di Scienze
Ambientali, Informatica
e Statistica

Ph.D. Programme in

Science and Management of Climate Change

36° cycle

Research Thesis

# Multi-risk assessment in coastal areas through the implementation of Artificial Intelligence methods

SSD: CHIM/12

**Ph.D. Coordinator**
Ch. Prof. Enrica De Cian

**Ph.D. student**
Maria Katherina Dal Barco
ID 871186

**Supervisor**
Ch. Prof. Andrea Critto

**Co-supervisors**
Ch. Prof. Sebastiano Vascon
Dr. Silvia Torresan

*To every woman in science:*
*your passion, strength and resilience*
*may one day be fully recognised.*

# Table of Contents

**Abstract** **4**

**Summary** **5**

**Chapter 1.** ***Introduction*** **7**

*1.1. Motivations and objectives*

*1.2. Outline of the thesis*

**Chapter 2.** ***Description of the case study area*** **10**

**Chapter 3.** ***First paper*** **13**

*A Machine Learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy)*

**Chapter 4.** ***Second paper*** **40**

*Integrating AI and climate change scenarios for multi-risk assessment in the coastal municipalities of the Veneto region*

**Chapter 5.** ***Third paper*** **65**

*Prioritise risks and improve adaptation strategies in the Veneto coastal area through the application of a custom AI tool*

**Chapter 6.** ***Conclusions*** **87**

**Annexes** **90**

**Acknowledgements** **95**

**References** **96**

# Abstract

Coastal areas are increasingly threatened by sea-level rise and shifting pattern of extreme events. In response to these complex dynamics, it is crucial to adopt integrated approaches that assess risks posed by both natural and anthropogenic stressors. The complexity of interactions between risk factors, combined with the availability of heterogeneous data, makes Artificial Intelligence (AI) and Machine Learning (ML) algorithms ideal tools to tackle multi-hazard and multi-risk assessments.

This thesis goes beyond traditional methods by exploring the advantages of AI-based tools, leveraging the potential of big data from open-source databases and local authorities through a series of articles focused on the coastal area of Veneto. In the first study, different ML algorithms were implemented to estimate daily coastal risks and identify the main factors driving impacts in the coastal municipalities of the Veneto region in the 2009-2020 timeframe. The most effective algorithm was enhanced in the second chapter with a two-tier approach to estimate impacts under different climate change scenarios up to 2100. The final paper introduces COAST-AId, a custom language model designed to analyse vast sets of information and facilitate coastal risk management, adapting EUCRA approach to identify intervention priorities for the Veneto littoral.

The results provide an assessment of the risks linked to extreme events in the Veneto coastal area, suggesting improvements to adaptation strategies.

# Summary

According to the IPCC scenarios, coastal areas face increasing risks due to rising sea levels and shifting patterns of extreme events. In response to these complex dynamics at the land-sea interface, coastal policymakers are seeking integrated approaches and tools to assess physical and environmental risks posed by both natural and human-induced stressors.

The availability of great volume of heterogeneous data – describing risk drivers such as weather observations, climate models, socio-economic data – along with complex hazard interactions and non-linear relationships between risk drivers and impacts, make Artificial Intelligence (AI) and Machine Learning (ML) algorithms particularly suitable to tackle multi-hazard and multi-risk assessment.

This Thesis goes beyond traditional methods by exploring the advantages of AI-based tools, leveraging the potential of big data provided by open-source databases and local authorities.

The first paper evaluates three different ML algorithms – Random Forest (RF), Multi-layer perceptron (MLP) and Support Vector Classifier (SVC) – to estimate daily coastal risks and identify key atmospheric and marine factors contributing to impacts in the coastal municipalities of the Veneto region in the 2009-2020 timeframe. Additionally, the coastal municipalities were clustered based on intrinsic relationships between impact occurrences, exposure, and vulnerability factors.

Building upon the best-performing algorithms from the first paper, the second paper proposes a two-tier approach to assess the effects of climate change on the Veneto coastal area over both the mid- and long-term. This approach incorporates three climate scenarios (RCP2.6, RCP4.5, RCP8.5) provided by EURO-CORDEX for the atmospheric variables and NASA for marine variables.

The final paper introduces COAST-AId, a custom Large Language Model (LLM), designed to facilitate the prioritization of risks and the enhancement of adaptation strategies in the coastal area of the Veneto region, following the risk assessment framework proposed by the European Climate Risk Assessment (EUCRA). This framework combines three key steps – i.e., risk identification, risk analysis, and policy analysis – to evaluate the urgency to act required to reduce major climate risks. To ensure the reliability of COAST-AId's outputs, its performance is evaluated by AI experts and local stakeholders, identifying challenges and opportunities for improving coastal resilience in the Veneto coastal area.

Key hazard factors identified include total daily precipitation, wind intensity, and maximum sea surface height, which were the primary drivers of coastal impact risks during the reference period. These risks are expected to increase, reaching their highest values by 2100. Notably, the projections differ across the RCP scenarios: under the low-emission scenario (RCP2.6), approximately 35

impacts per year are expected by the end of the century. This rises to 50 impacts per year under the mid-emission scenario (RCP4.5), and 60 impacts annually under the high-emission scenario (RCP8.5). The urgency evaluation, performed through the application of COAST-AId, began with the identification of climatic (e.g., sea-level rise, extreme precipitation) and non-climatic drivers (e.g., land-use changes, subsidence) responsible for coastal risks in the Veneto region – i.e., coastal flooding, coastal erosion, permanent inundation and saltwater intrusion. The results indicate that coastal flooding and coastal erosion are expected to have the most severe impacts, while coastal flooding and permanent inundation require the most immediate attention.

The tools developed in this research are designed to be powerful instruments for local authorities and decision-makers, enabling their understanding in evolving risk dynamics and predict risk occurrences. For this reason, the results represent an early prototype of a decision support tool that could underpin climate change risk assessment and guide the definition of adaptation strategies at the regional scale, not only for the Veneto region, but also for other regions with different environmental and socio-economic contexts.

The activities carried out in this research were conducted as part of the Interreg Italy-Croatia AdriaClim and Horizon2020 MYRIAD-EU projects, which aimed at developing a multi-risk approach to assess coastal impacts in the Veneto pilot area.

# Chapter 1. *Introduction*

## 1.1. Motivations and objectives

The scientific community widely acknowledge that climate change is causing severe impacts on terrestrial and marine ecosystems worldwide. In particular, climate-related impacts will be especially severe across coastal areas, where a dense interaction between terrestrial and marine systems occurs (IPCC, 2021, 2023). Based on climate change scenarios developed by the Intergovernmental Panel on Climate Change (IPCC), coastal areas and related ecosystems will be increasingly exposed to intense climate related impacts as a direct consequence of rising sea levels and changing patterns, frequency and intensity of extreme events (e.g., coastal storms, floods; MATTM, 2017). These phenomena are projected to increase in the future leading to more severe environmental effects (IPCC, 2018), including water quality deterioration, biodiversity loss, reduced species survival and shift which, in turn, will affect ecosystems services flow and generate socio-economic damages (UNDP, 2010). Besides climate-related treats, coastal areas are also experiencing relevant pressures resulting from multiple anthropogenic pressures linked with coastal economic development (e.g., fishing, sands extraction, tourism, urbanization, infrastructures; Halpern et al., 2019; Lonsdale et al., 2020; Stock et al., 2018) and population growth. It is well known as higher population densities can be mainly recognized along coastal cities (IPBES, 2018; Singh et al., 2019) where, during the summer season, population increases even more as a result of tourism (Anderies & Barreteau, 2019).

Against the complex interplay between human-made and climate change pressures occurring at the land-sea interface, coastal authorities and policymakers are increasingly faced with the challenging task of balancing coastal development with risk management. An integrated approach to coastal multi-risk assessment and management is needed. This approach must combine technical and scientific studies to, on one side, identify the main drivers of coastal imbalance and, on the other, design the most suitable adaptation and management measures. Furthermore, this integrated approach should align with policy directions described in the EU Strategy on Adaptation to Climate Change (2021), which supports the development of adaptation strategies at all levels of governance, especially the local level, by promoting data-driven climate services and identifying nature-based solutions for adaptation. It also should reflect the goals of the EU Mission on Adaptation to Climate Change (2021), which emphasises addressing climate risks through more systemic and accelerated adaptation actions, while covering different geographical scales and addressing common topics (e.g., coastal risk, landscape planning; EUCRA, 2024).

In recent years, Artificial Intelligence (AI) tools have been increased employed to improve the analysis of climate hazards and their interactions, while enhancing the understanding of climate

change risks (Zennaro et al., 2021). In this sense, AI and big data analytics—such as climate model outputs, earth observations, and exposure and vulnerability datasets—have been widely applied to analyse complex, climate-driven, multi-risk dynamics across various sectors, regions, and timeframes (Castruccio & Genton, 2018; Fogarin et al., 2023; Pham et al., 2023, 2024). Despite the huge potential of these tools, relatively few studies have combined AI and Machine Learning (ML) algorithms with multi-risk assessment in coastal areas, leaving a gap in the understanding of the linkages between impacts and their drivers (Nieves et al., 2021; Park & Lee, 2020a).

This Thesis aims to fill this gap by proposing the implementation of three different AI-based tools to empower coastal multi-risk assessment and provide guidance for integrated coastal zone management and adaptation planning along the coastal areas of the Veneto region (Italy), one of the identified hotspots of climate change (EUCRA, 2024). The multi-risk assessment proposed is part of a broader risk assessment procedure that builds upon and draws inspiration from international and European risk assessment guidelines in the field of climate change adaptation and disaster risk reduction (EC, 2019; EEA, 2018; Poljansek et al., 2019) and on the international ISO standard (ISO, 2018). In particular, the coastal area of the Veneto region is first examined within the 2009-2020 historical timeframe to analyse coastal risks related to extreme weather events, and then to estimate future coastal impacts under mid-term and long-term scenarios (i.e., 2045 and 2100, respectively) integrating projected climate change conditions. Finally, the prioritization of risks and adaptation strategies is performed identifying current gaps and detecting areas needing further improvement.

Given all, the objective of this Thesis is to address the following three research questions:

(1) *Which are the main drivers of coastal risks along the municipalities of the Veneto region that can be identified through the implementation of Machine Learning algorithms?*

(2) *How accurately can AI methods estimate the frequency of future extreme weather events in the coastal municipalities of the Veneto region, based on historical and climate data?*

(3) *How can Large Language Models assist in enhancing climate adaptation strategies for coastal communities in the Veneto region, considering the multiple risks they face?*

## 1.2. Outline of the thesis

This Thesis comprises three independent research papers to respond to the research questions.

The first research question is addressed in the first paper titled "*A Machine Learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy)*" and published in the *International Journal on Disaster Risk Reduction*. This paper evaluates three different Machine Learning (ML) algorithms – i.e., Random Forest (RF), Multi-layer perceptron (MLP) and Support Vector Classifier (SVC) – to identify the most important atmospheric and marine factors which led

to the occurrence of impacts along the coastal municipalities of the Veneto region in the historical period (2009-2020).

The second paper, titled "*Integrating AI and climate change scenarios for multi-risk assessment in the coastal municipalities of the Veneto region*", is published in *Science of the Total Environment* journal. It attempts to answer to the second research question on the estimation of future impact trends. To this aim, this paper presents an improved version of the ML model developed within the first paper, thus proposing a two-tier approach able to estimate, on one side, the occurrence of impacts caused by extreme events and, on the other, their frequency against future climate change conditions. The application incorporates the indicator projections developed in the frame of the Interreg Italy-Croatia AdriaClim project (i.e., AdriaClim-WRF) and retrieved from the EURO-CORDEX simulations. In particular, the first set is employed to reveal the importance of each combination of stressors under the worst Representative Concentration Pathway scenario (i.e., RCP8.5), thereby uncovering the non-linear effects of compounding hazards within the mid-term period (until year 2045). On the other hand, the second set of simulations collects the information related to three different emission scenarios (i.e., RCP2.6, RCP4.5 and RCP8.5), enabling a broader overview of the expected frequency of coastal impacts until the end of the century.

Finally, the last research question is explored in the third paper titled "*Prioritise risks and improve adaptation strategies in the Veneto coastal area through the application of a custom AI tool*", which was recently *submitted* to a high-impact peer-reviewed journal. This application aims at supporting local decision-makers facilitating the prioritization of risks and adaptation strategies, downscaling the most recent European and international risk assessment guidelines (EUCRA, 2024; IPCC, 2023; ISO, 2018). To reach this goal, a custom Large Language Model (LLM), called *COAST-AId*, is developed to analyse an extensive collection of documents, reports and scientific applications implemented within the coastal area of the Veneto region. This information enables the (i) identification of the most relevant coastal risks for the Veneto region, (ii) analysis of the severity of these risks, and (iii) evaluating current policies and adaptation strategies. Validated by local stakeholders, they are integrated in the EUCRA matrix to calculate the urgency to act for each risk in the Veneto coast, offering insights to enhance local policies and paving the way for resilient management plans.

The conclusive section aims at providing a comprehensive summary of the key findings derived from the aforementioned applications. This section not only highlights the strengths and limitations of the research, but also offers a critical evaluation of the methodologies implemented and the results obtained. Additionally, potential future developments are outlined, suggesting possible improvements to the current approaches and offering a clear direction on how the research can be refined to better address the challenges and opportunities identified.

# Chapter 2. *Description of the case study area*[1]

The Veneto region features a highly heterogeneous landscape (Figure 1a), resulting in distinct hazards impacting various areas of the region (Zonn et al., 2021). The mountainous zones (related to the provinces of Belluno, Verona, and Vicenza) are predominantly affected by landslides, particularly during heavy rainfall events (Franceschini et al., 2022; Meena et al., 2022). The inland plains, included in the provinces of Padova, Verona and Vicenza, are primarily affected by river floods, which are exacerbated by intense precipitation and snowmelt (Mel et al., 2020; Pantalona et al., 2021). The water quality degradation is of critical concern in the Lagoon of Venice, due to anthropogenic pressures and hydrological modifications (Aslan et al., 2022; Zennaro et al., 2023). Finally, *the coastal area of the Veneto region*, the focus of this study, faces multiple hazards, including pluvial and coastal floods, sea-level rise, coastal erosion, and storm surges (Carbognin et al., 2010; Cavaleri et al., 2020; Fogarin et al., 2023; Lionello et al., 2021; Pham et al., 2024; Regione Veneto, 2024).

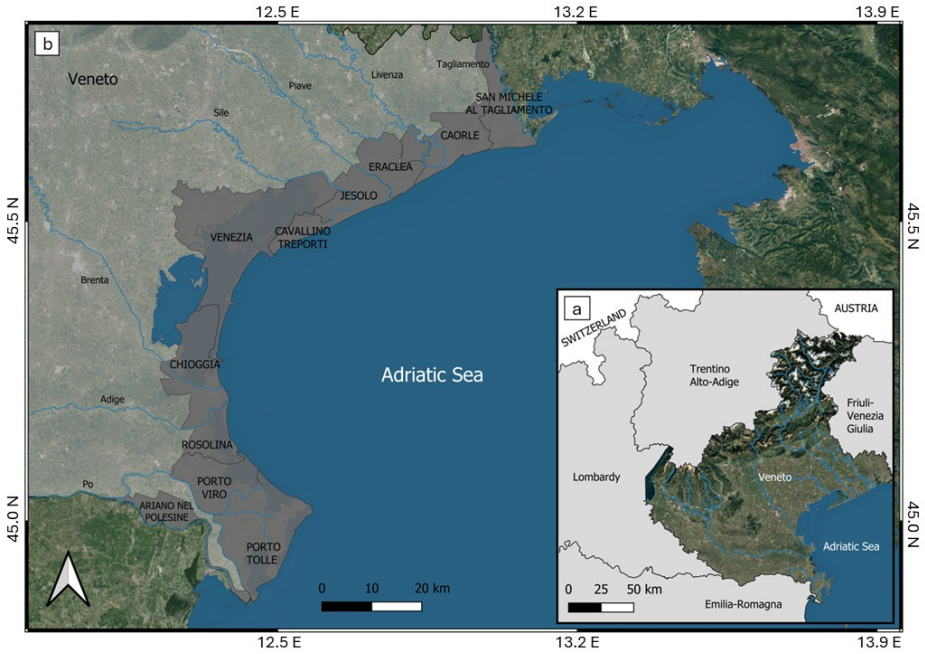



*Figure 1. Case study area: (a) The geographical context of the Veneto region, showing its location in northeastern Italy, and (b) the coastal municipalities of the Veneto region analysed in this study.*

The study area covers the eleven coastal municipalities of the Veneto region (Figure 1b), facing the Adriatic Sea along approximately 169 km of coastline (Ruol et al., 2016). These are located in the provinces of Venice - San Michele al Tagliamento, Caorle, Eraclea, Jesolo, Cavallino-Treporti,

[1] This Chapter is derived from Dal Barco et al., 2024: "A Machine Learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy)", published in *International Journal on Disaster Risk Reduction*, Volume 108, May 2024, 104526. https://doi.org/10.1016/j.ijdrr.2024.104526; Dal Barco et al., 2025: "Integrating AI and climate change scenarios for multi-risk assessment in the coastal municipalities of the Veneto region", published in *Science of the Total Environment*, Volume 965, February 2025, 178586. https://doi.org/10.1016/j.scitotenv.2025.178586; and Dal Barco et al., "Prioritise risks and improve adaptation strategies in the Veneto coastal area through the application of a custom AI tool", submitted to *Communications Earth & Environment*.

Venice, Chioggia - and Rovigo - Rosolina, Porto Viro, Porto Tolle, Ariano nel Polesine; ISTAT, 2021). The Po and Tagliamento rivers define the region's southern and northern borders, respectively. The coast is divided into three distinct morphological zones (Bezzi et al., 2018). The northern part is characterised by straight, sandy, and low-lying littorals shaped by the Sile, Piave, Livenza, and Tagliamento rivers (Zonn et al., 2021). The central area is dominated by the Venetian Lagoon whose original morphology was altered by historical river diversions. The Sile and Brenta rivers, which once flowed into the lagoon, were redirected during the Middle Ages to mitigate frequent catastrophic floods (Bellizia et al., 2023). Today, the lagoon is delimited by the sandy barrier islands of Lido di Venezia and Pellestrina (Zonn et al., 2021). The southern part of the coast features the Po river and its Delta, a complex system of river branches, outlets, and salt marshes, recognised as one of the most ecologically significant areas in the Veneto region (Ruol et al., 2018; Torresan et al., 2008). Despite multiple sediment inflow, the Veneto coastline has been undergoing massive coastal erosion due to urbanisation and anthropic pressure during the last century, considerably changing the overall natural land-use due for urbanisation, industrialisation, and tourism purposes, which have significantly altered the natural sediment balance, reducing the resilience to coastal hazards (Legambiente, 2012). From a socio-economic perspective, coastal capital is driven by fisheries, aquaculture, agriculture, industrial activities, maritime traffic, offshore activities and tourism (Torresan et al., 2012). The latter is made possible by the mild climate that the Veneto region offers throughout the year due to its proximity to the Adriatic Sea, as well as the presence of diversified landscapes (e.g., mountains, lakes, hills) and numerous UNESCO sites across the territory (Cuccia et al., 2016). Looking at the coastal area of the Veneto region, it belongs to the subcontinental temperate zone (Barbi et al., 2013), with higher average annual temperatures (about 14°C) than the inland areas (around 13°C; Barbi et al., 2013). Moreover, the area records a lower number of rainy days with an overall lower rainfall accumulation, but a higher number of days with heavy precipitation (Barbi et al., 2012).

The historical exposure of the Veneto coastal area to various natural and anthropic pressures has been exacerbated even more in recent decades by climate change. This unique geomorphology renders the region particularly susceptible to extreme events as a result of a multitude of hazards (Camuffo, 2021; Cavalieri, 2020; Legambiente, 2012; Lionello et al., 2020; Zanchettin et al., 2020). The increase of mean temperature (about 0.55°C per decade) and heatwave events, combined with the intensification of rainfalls, strong winds, and extreme sea-level events, have amplified coastal related risks, impacting water quality, biodiversity, and the livelihoods of local communities (Ferrarin et al., 2013, 2022; Fogarin, Zanetti, Dal Barco, et al., 2023; Lionello et al., 2020; Umgiesser et al., 2021).

Recent notable extreme events include the exceptional high tide of November 2019 and the compound hazard events that led to the Vaia storm (also known as Storm Adrian) between October and

November 2018 (Lionello et al., 2020). The November 2019 high tide was driven by a combination of atmospheric and oceanographic factors, including strong Sirocco winds across the Adriatic basin, a peak in the astronomical tide, an unusually high average sea-level in the Adriatic and the passage of a small cyclone over the Northern Adriatic and the Venice lagoon (Lionello et al., 2020). The Vaia storm, a powerful Mediterranean storm with hurricane-force wind gusts and heavy rainfall, predominantly impacted the mountainous areas of the Veneto region, causing extensive forest destruction (Laurin et al., 2021). It also triggered an unusually prolonged high tide in Venice, leading to storm surge events along the coastline and sediment overflow at the Veneto river mouths (Biolchi et al., 2019).

In response to these unprecedented multi-hazard and multi-risk scenarios, various strategies have been implemented to safeguard coastal zones and enhance urban resilience. The most implemented measures, aimed at managing coastal-related risks, include both 'grey infrastructure', such as groins, breakwaters, and tidal gates, as well as 'nature-based solutions' like beach nourishment, dune restoration and conservation of natural areas (Regione del Veneto, 2024). Recently, the Environment and Ecological Transition Unit of the Veneto Region drafted the prelimary document of the Regional Strategy for Climate Change Adaptation (SRACC; Regione del Veneto, 2024). The SRACC outlines an adaptive framework tailored to the region's diverse geographic and environmental features, encompassing alpine, riverine, lacustrine and coastal areas.

The strategy has been conceived as a strategic document built upon the findings of five technical-scientific reports[2], which provide a comprehensive foundation on climatic conditions, existing adaptation plans, and multi-hazard analyses related to climate change. Notable, indices have been developed to classify relative risk levels across multiple climate-related hazards in the Veneto Region (Regione del Veneto, 2024). Among these risks, coastal flooding is the only coastal risk explicitly addressed in the current strategy, with its impacts projected to intensify significantly due to climate change, leading to an increased number of affected receptors (Regione del Veneto, 2024). However, the land-sea interface in the Veneto region is exposed to a broader spectrum of critical coastal risks that remains unaddressed (Fogarin, Zanetti, Dal Barco, et al., 2023; Tosi et al., 2022). This study aims to fill this gap by conducting a comprehensive analysis of coastal risks in the Veneto region. Specifically, it aims to identify and prioritise the major coastal risks and to offer robust evaluation guidelines that could inform regional adaptation and risk management planning processes, making them effectively respond to the complex and evolving challenges posed by climate change.

[2] Technical-Scientific Reports produced to support the Veneto Region Strategy for Climate Change Adaptation (SRACC): https://www.regione.veneto.it/web/ambiente-e-territorio/rapporti-tecnico-scientifici.

# Chapter 3. *First paper*[3]

# A Machine Learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy)

**Abstract.** A significant and unprecedented increase of temperature has been recorded worldwide during the last decades, leading to the occurrence of numerous extreme events. Coastal areas, with their high population density, interconnected economic activities, fragile ecosystems, are particularly vulnerable to climate change impacts. These impacts can be intensified by the interactions of multiple hazards which operate at different spatio-temporal scales and affect exposure and vulnerability patterns. An integrated approach is here proposed to assess the relationship between risk factors and to evaluate the multiplicity of impacts that may affect the coastline. A new path to tackle these multi-risk events is offered by ML algorithms to effectively handle vast amounts of heterogenous data, and model complex non-linear relationships between multiple factors and feedback mechanisms. To assess impacts caused by extreme events (storm surges, extreme precipitation, wind events) in the Veneto coastal municipalities, a ML approach was developed to understand connections between atmospheric and marine hazards and impacts recorded by the Veneto region emergency archive during the 2009–2019 timeframe, identifying the most influencing factors triggering multiple risks. Additionally, the coastal municipalities were clustered considering the intrinsic relationships between impact occurrences, exposure and vulnerability features. Several algorithms were compared to estimate daily risk of impacts to occur providing hazards, exposure and vulnerability information. The MLP algorithm showed satisfactory performances (weighted-F1-score of 0.94) to estimate the relative importance of input features. The proposed algorithm was designed as support tool to increase the understanding of impacts' occurrence in coastal areas, thus helping the adaptation planning process.

[3] This Chapter is derived from Dal Barco et al., 2024: "A Machine Learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy)", published in *International Journal on Disaster Risk Reduction*, Volume 108, May 2024, 104526. https://doi.org/10.1016/j.ijdrr.2024.104526.

## 3.1. Introduction

Over the past three decades, the global climate has experienced a significant and unprecedented increase of temperature (IPCC, 2021, 2023). According to the results of climate models, global surface temperature is projected to further increase up to 4°C by the end of this century (IPCC, 2021, 2023), exacerbating changes in ecosystem functioning (Schickhoff et al., 2016; Weiskopf et al., 2020) and leading to the occurrence of many extreme events worldwide (AghaKouchak et al., 2020; IPCC, 2021, 2023; Sorokin, 2018). Both the frequency of high-temperature events (i.e., hot days and nights) and extreme rainfall events (triggering pluvial and fluvial floods) have already increased in many parts of the world (AghaKouchak et al., 2020; Goswami et al., 2006; IPCC, 2021, 2023; Vecere et al., 2021). Similarly, in many regions, the number of rainy days has significantly decreased causing severe water scarcity and drought conditions (Weiskopf et al., 2020). As multiple hazards may interact and affect the environment and the society in complex ways, there is the need for improved climate risk methods and tools to better understand and anticipate consecutive, co-occurring or interacting hazards affecting the same territory.

This is particularly important in coastal areas where land, sea and climate-related hazards interact at different spatial and temporal scales, leading to compound and cascade impacts on society ad ecosystems (Zscheischler et al., 2020). Given the multi-risk nature of the problem at stake, as well as the non-linear interactions of exposure, vulnerability, and hazard factors, a major scientific effort to enhance current methodologies and capabilities to better assess climate risks from regional to local scales and predict their impacts on society and ecosystems is needed.

In recent years, Machine Learning (ML) approaches have been increasingly applied to model climate change risks, given their capacity to analyse complex interactions and feedback structures, exploiting the availability of big and heterogenous volumes of data (Zennaro et al., 2021). Given the complexity of the coastal system, ML methods started to be implemented to capture the relationships between the natural and anthropic pressures, thus understanding the consequences of such interactions. At first, Bayesian Networks (BN) have been developed as a surrogate of more complex physical-mathematical models, for translating marine offshore hazards into damages at the coastal receptors (Bolle et al., 2018; Dal Barco, Furlan, et al., 2024; Ferreira et al., 2019; Jäger et al., 2018; Pham et al., 2024; Plomaritis et al., 2018; Sanuy & Jiménez, 2021). In particular, Jäger et al. (2018) considered four receptors (i.e., residential properties, commercial properties, people, and saltmarshes) affected by different hazards (e.g., flood depth, wave height). Sanuy & Jiménez (2021) perfectioned the approach by training the dataset with real storms data, thus decreasing the uncertainty associated to the use of synthetic events. Moreover, by splitting the BN into two parts, the authors were able to

consider the variability of the forcing conditions (solving the source–consequence relationships), while examining the spatial distribution of the receptors.

On the other hand, rapid and extreme weather events have been analysed by Park and Lee (2020), who developed a risk probability map for evaluating flooding in the coastal areas of South Korea. Different classification ML methods, including k-Nearest Neighbor (kNN), Random Forest (RF), and Support Vector Machine (SVM), were compared to predict the presence or the absence of flooding, in relation to hazard, exposure and vulnerability features (e.g., tide, precipitation, elevation, slope, land-use) (Janizadeh et al., 2021; Rana & Mahanta, 2023; Sampurno et al., 2022). Building upon this research area, here a ML model was developed and applied to the coastal municipalities of Veneto region (Italy) in order to estimate the potential risks associated to climate change and extreme weather events in coastal areas, given a set of atmospheric and marine indicators. Specifically, the designed model is able to associate a risk score to each day and municipality in the Veneto costal area given the knowledge of the indicators, where a risk score is a measure of the likelihood that an impact occurs, where impacts includes both damages (e.g., agricultural losses, shoreline erosion, damage to buildings) and services interruption (e.g., blackouts, impaired viability), caused by extreme climate events. Once trained, the model can determine the importance of the different factors that lead to the recorded impacts. For this purpose, several Supervised ML models (i.e., algorithms whose parameters are estimated using data for which both the input features and the output labels are known, such as Random Forest, Neural Networks and Support Vector Machines), have been implemented. These algorithms are able to model interactions between different factors using data from past historical events and cope well with the high number of parameters involved in the risk analysis (Chen et al., 2020).

Overall, in multi-risk applications, algorithms like Random Forest, Decision Trees and Bayesian Networks are more commonly applied than Deep Learning techniques, mainly due to their simpler implementation and interpretation (Zennaro et al., 2021). Support Vector Machine and Multi-Layer Perceptron algorithms are often included as benchmark for evaluating classification and regression performances of other more complex models, due to their efficiency, together with classical statistical algorithms, like Logistic Regression and Generalised Additive Models (GAM), which instead offer more interpretable frameworks, while being still able to cope with the non-linear nature of the risk drivers' relationships (Terzi et al., 2019). Deep Learning models instead are more often applied to Early Warning Systems applications, studies that focus on hazard predictions and forecasting or research leveraging earth observations data or social media data, where harnessing big data can really play a big role. Multi-risk applications need to integrate hazard, vulnerability and exposure drivers, often at different spatio-temporal resolution and are constrained by the scarceness and coarseness of

impact data, which further limits the possibility to leverage Deep Learning models (Huntingford et al., 2019; Tilloy et al., 2019).

One of the challenges of the problem at hand is the skewness of the input dataset (i.e., the presence of many more impact-free days compared with the number of days with impacts). This problem is common to several fields (Malik & Ozturk, 2020), including weather predictions (de Coste et al., 2022; Rao et al., 2020), political science (Hegelich, 2016), manufacturing failure (Dogan & Birant, 2021), medical examinations (Luca et al., 2014), fraud detection (Yousefi et al., 2019), finance (Coffinet and Kien, 2019), and social science (Hain & Jurowetzki, 2020). This issue was addressed by applying weights that increase the importance of the minority class, as done in most of these papers.

Following the collection and the analysis of available data (Section 3.2), the implemented ML algorithms are described (Section 3.3), and the main findings resulting from their application in the Veneto region case are summarised, and the strengths and weaknesses of the proposed approach are discussed (Section 3.4). In the discussion, suggestions on future model improvements to respond to other EU directives related to water resource assessment and management, including modelled data, are proposed (Section 3.5).

## 3.2. Data collection

The implementation of the ML model requires information of the occurrence of impacts related to extreme weather events along the coastal municipalities of the Veneto region during the 2009-2019 decade with daily temporal resolution. In particular, for each municipality and for each day, a series of indicators (or features), which constitute the input variables of the algorithm, as well as the output labels (a Boolean indicator which describes the presence/absence of impact) were collected. These indicators are a set of spatio-temporal heterogeneous variables that can influence the likelihood of an impact to occur in the investigated area (Cavaleri et al., 2020; Crespi et al., 2020; Lionello et al., 2020; Pham et al., 2024; Zanchettin et al., 2020), and are mainly related to hazards, seasonality and location. Moreover, exposure and vulnerability characteristics are collected to be jointly analysed with the ML results.

The collection of the input features related to exposure and vulnerability, hazards, and impacts, are detailed in Table 1.

*Table 1. Summary of input data used for the Machine Learning application in the Veneto coastal area.*

| Data category | Indicator | Spatial domain | Spatial resolution | Timeframe | Temporal resolution | Source |
|---|---|---|---|---|---|---|
| *Exposure and vulnerability* | Total area | Veneto region | Municipality | 2022 | unique value | ARPAV[4] |
| | Land-use type | Italy/EU | 1km | 1990 – 2020 | multi-year | JRC – LUISA platform[5] |
| | Population | | | | | JRC – LUISA population[6] |
| | Soil characteristics | Veneto region | 1:50.000/ 1:250.000 | 2022 | unique value | ARPAV Geoportal[7] |
| | Topography | Italy | 10m | 2017 | unique value | (Tarquini et al., 2007; Tarquini et al., 2017) |
| *Atmospheric hazards* | Total precipitation<br>Wind speed<br>Humidity | Veneto region | Coastal monitoring stations | 2009 – 2019 | hourly, daily | ARPAV[4] and ESWD[8] |
| *Oceanographic hazards* | Sea surface height<br>Significant wave height | Mediterranean Sea | 1/24° (~ 4km) | 1987 – 2023 | hourly, daily | CMEMS[9] |
| *Impacts* | Damages and service interruption | Veneto region | Municipality | 2009 – 2019 | daily | Veneto Region[10] |

### *3.2.1. Exposure and vulnerability characteristics*

To support the analysis of the factors that drive the occurrence of impacts and try to understand the underlying multi-risk dynamics, the exposure and vulnerability characteristics of the coastal municipalities of the Veneto region were collected.

The total area of each municipality, the land-use types (i.e., anthropic, agriculture, natural, water bodies), soil characteristics (i.e., permeability, dune ridges and lagoon islands, reclaimed lagoon areas artificially drained), population (i.e., total population and density), and topography (i.e., elevation, slope) were studied. In particular, the municipality extension deserves a special mention, as it is reasonable to expect that bigger municipalities are affected by more impacts. However, it is impossible to normalize the number of days with impacts using the municipality size, as it is not recorded if more than one impact happens on a given day. Topography data of the study site were derived directly from the Digital Elevation Model (DEM) of 10m x 10m obtained by the National

[4] Regional Environmental Protection Agency of the Veneto region (ARPAV): https://www.arpa.veneto.it/dati-ambientali/open-data.
[5] Land Use-based Integrated Sustainability Assessment (LUISA) modelling platform developed by the European Commission's Joint Research Centre (JRC): https://data.jrc.ec.europa.eu/collection/luisa.
[6] Land Use-based Integrated Sustainability Assessment (LUISA) modelling platform for population developed by the European Commission's Joint Research Centre (JRC): https://data.jrc.ec.europa.eu/dataset/jrc-luisa-population-ref-2014.
[7] Geoportal developed by the Regional Environmental Protection Agency of the Veneto region (ARPAV): https://gaia.arpa.veneto.it/.
[8] European Severe Weather Database (ESWD): https://eswd.eu/.
[9] Copernicus Marine Service (CMEMS): https://doi.org/10.25423/CMCC/MEDSEA_MULTIYEAR_PHY_006_004_E3R1.
[10] Veneto Region – Post-Emergency Disaster Events Management Office: https://bur.regione.veneto.it/BurvServices/Pubblica/sommarioDecretiPGR.aspx?expand=19.

Institute of Geophysics and Volcanology (Tarquini et al., 2007; Tarquini & Nannipieri, 2017). Data on soil types and permeability were retrieved from ARPAV Geoportal[4]. Population and land-use data were collected from the JRC web portal.

As the exposure and vulnerability indicators are almost constant over time, and only one value per municipality is available, in the ML framework their contribution to the creation of the impact is conveyed by the municipality index. In other words, it is possible to estimate the influence that each municipality has in creating the impact, but it was not possible to determine which of the exposure and vulnerability factors are playing a major role. For this reason, the only indicator used as input for the ML model related to exposure and vulnerability is the municipality index. Although exposure and vulnerability features are not directly used as input data for the Machine Learning, the description of these indicators is included in this study to contextualise the interpretation of the results (Section 3.4.3.2).

### *3.2.2. Hazard input features*

In order to estimate the impacts along the Veneto coastal municipalities, the ML-based tools are trained on hazard-related indicators, such as atmospheric (i.e., precipitation, wind, humidity) and oceanographic features (i.e., sea surface height and significant wave height). The hazard information is related to the day when the impact did/did not occur, as well as to the 3 days just before, as some cascading effects can be delayed (Lionello et al., 2012; Raveh-Rubin & Wernli, 2015).

The atmospheric data were derived from the monitoring network of the Regional Agency for Environmental Protection and Prevention of the Veneto Region (ARPAV), which acquires precipitation, temperature, humidity and wind data at hourly or daily basis. Each municipality has at least one monitoring station, except for Jesolo, Porto Viro, and Ariano nel Polesine (Figure 1). Considering the proximity of the municipalities and the low variation in the values of the atmospheric parameters, in accordance with the data provider, the nearest neighbour rule was applied to infer their atmospheric conditions in the missing stations. In particular, in Jesolo and Porto Viro the missing entries are filled with the average of the values measured by two closest stations, while in Ariano nel Polesine, which borders another region, they are replaced with the values measured in the nearest station. On the other hand, Venezia has two stations within its territory, and similar values were recorded. However, since the Favaro Veneto station has more missing entries than the Venezia - Istituto Cavanis, the latter was selected to represent the municipality. Additionally, wind indicator data from the monitoring stations has been integrated with information from the European Severe Weather Database5, as local events (e.g., tornadoes) may not be detected by the stations.

Oceanographic hazard indicators for the Veneto pilot were collected from the Copernicus Marine Service (CMEMS) provided by the European Union's Earth Observation Programme. The above-mentioned indicators were retrieved from the Mediterranean Sea Physics Reanalysis database (i.e., MEDSEA_MULTIYEAR_PHY_006_004)[6], which is the product of a numerical composed hydrodynamic model, supplied by the Nucleus for European Modelling of the Ocean (NEMO)[11] and a variational data assimilation scheme (OceanVAR)[12]. Specifically, the sea surface height and the wave height data are available on a regular grid of 1/24° (about 4 km) at hourly resolution. The values of the closest pixels to the municipalities' coastline were extracted and aligned with the local data at the *Acqua Alta* platform.

### *3.2.3. Impact data*

The impact data indicator includes both damages (e.g., agricultural losses, shoreline erosion, damage to buildings) and services interruption (e.g., blackouts, impaired viability), caused by extreme climate events within the coastal municipalities of the Veneto region. The list includes events that are severe enough to trigger the 'State of crisis' (i.e., Stato di crisi) in some coastal municipalities of the Veneto region, i.e., events that for intensity and extension require an immediate response from the regional authorities. This information is retrieved from Decreto del Presidente della Giunta Regionale reports (DPGR, namely Decree of the President of the Regional Council). For each impact, these documents provide qualitative information on the reported damages, the list of the municipalities affected and the dates when the impact took place. Typologies of the damages reported include physical damages related to urban flooding, agriculture/fisheries, people (e.g., fatalities, injuries, displacements), beaches (e.g., shoreline erosion, debris accumulation), structures/infrastructures, economic activities, and tertiary sector. Ideally, in order to accurately determine the quantitative extent of impacts, more detailed data and reports on the investigated extreme event, including coordinates, typology, monetary cost of restoration would be required. However, detailed quantitative data on impacts and their economic costs are not in the public domain. Therefore, the impact dataset is a set of couples (day, municipality) where an impact occurred.

Unfortunately, the impacts collected in the 'Stato di crisi' reports may be incomplete and misleading: not all impacts that created an economic loss or a service interruption have been filed. On the other hand, each 'Stato di crisi' report lists a series of municipalities and a series of dates but does not explain in which date each municipality was affected. Similarly, the typology of damage, when

[11] Nucleus for European Modelling of the Ocean (NEMO) model: https://www.nemo-ocean.eu/.
[12] Variational ocean (OceanVar) data assimilation system developed at the Euro-Mediterranean Center on Climate Change (CMCC): https://www.cmcc.it/models/oceanvar.

present, is not associated to a specific date or municipality, making this information impossible to be used.

To identify the correct coupling between dates and municipalities, and therefore reduce the errors in the input dataset, each impact has been checked against local newspapers. Additionally, local newspapers have also been used to identify events that were not reported in the 'Stato di crisi' database, but still led to damages to population or infrastructures. Eventually, the impact dataset comprises a total of 447 days of impacts from extreme weather events over eleven Veneto coastal municipalities during the 2009-2019 timeframe.

## 3.3. Methodology

The objective of this study is to understand the dynamics that generate the occurrence of impacts, with the aid of a tool able to calculate a risk score for each sample (day, municipality), which is a measure of the likelihood that an impact occurs in that municipality on that day, given the corresponding set of atmospheric and marine indicators. The different methodological steps to achieve this goal are depicted in Figure 2. The first step is related to the data collection (already described in Section 3.2. The collected data are then cleaned and analysed (Section 3.3.2) to have a preliminary idea of the dynamics involved. In parallel, the performance metric that will be used to measure the quality of the algorithms needs to be chosen (Section 3.3.3.1). The cleaned data and the performance metric are jointly used to design, train, tune, validate, and test several ML algorithms (Section 3.3.3.2). These can be used to create a decision support tool for risk assessment, and to estimate the importance of different hazard factors (Section 3.3.3.3), which is then compared with the results of the data analysis to gain insight into the physical drivers of the phenomena, hence contributing to the implementation of adaptation planning.

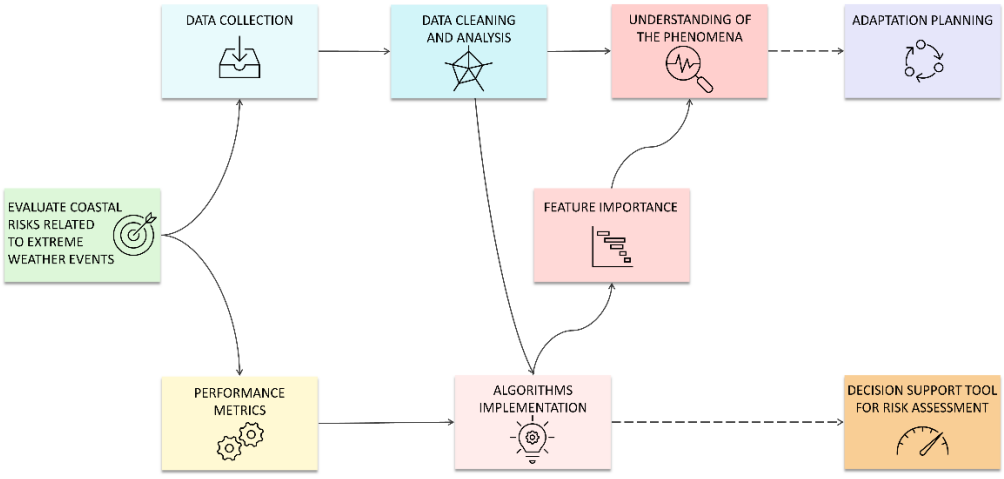



*Figure 2. Operative steps adopted to estimate the risk score and the most influencing features in the reference timeframe (2009–2019) for the Veneto coastal municipalities.*

### *3.3.1. Exposure and vulnerability feature analysis*

The analysis of exposure and vulnerability factors is aimed at understanding the intrinsic characteristics of the investigated case study, highlighting the territorial peculiarities that could intensify the effects of extreme weather events.

Once collected (Section 3.2.1), the exposure and vulnerability data were extracted as average value for each municipality and normalized. The resulting output of this analysis is detailed in Section 3.4.1.

### *3.3.2. Data wrangling, cleaning and analysis*

The collected input data for ML (i.e., hazard indicators, location, seasonality, impacts) need to be transformed and cleaned from one raw to into a structured format, with the intent of improving data quality and make it more suitable as input for the algorithm (data wrangling): each sample of this dataset is related to a couple (day, municipality), and one and only one value for each indicator is associated to each sample. Each sample in the input dataset also contains the corresponding output label, indicating the presence or absence of impact. All samples, whose output label is 1 (an impact occurred on the corresponding day and municipality), are referred to as positive event and belong to the positive class. Specularly, all samples whose output label is 0 (no impact occurred on the corresponding day and municipality) are referred to as negative event and belong to the negative class.

Initially the collected hazard indicators list included a wide range of variables: daily precipitation (maximum in one hour and cumulative during a day), maximum number of consecutive dry days, number of days with cumulative precipitation exceeding that of the 95th percentile, maximum cumulative precipitation in 1 day, maximum and minimum temperature, number of heat waves, heat wave temperature, number of tropical nights, number of hot days, humidity, wind velocity (maximum and average) and direction, sea water velocity and direction, wind wave height, maximum wind wave height, wind wave direction, sea surface wind wave mean period, mean and maximum sea surface height. This list of indicators contains redundant information, as indicators are not independent from each other. Moreover, the low quantity and quality of impact data suggested to reduce the number of input indicators to avoid the risk of overfitting.

In order to reduce the number of input variables without affecting the quality of results an iterative procedure was set in place: first, all collected hazard indicators were used to train the algorithm, and the algorithm performance was evaluated on the validation dataset and the feature importance was calculated; this process was repeated several times in order to have an average performance of the algorithm. Then, the indicators that scored lower in the feature importance were gradually removed

from the input indicators, the algorithm was retrained, and the performance validated: if the new performance was better or equal to the performance obtained before removing the indicators, the indicators were considered superfluous. This process was repeated until only indicators whose presence improved the performance were left. The final list of input indicators is summarised in Table 2.

The following data cleaning process consists in filling out missing data and identifying potential errors; this step is necessary, as its correct execution has major effects on the performances of the model.

Finally, the conditional distributions of the indicators given the presence/absence of impacts were analysed. This analysis is meaningful as every supervised learning algorithm relies, although in different ways, on the differences of these conditional distributions.

*Table 2. List of input indicators to characterize the Veneto coastal case study.*

| Acronym | Definition |
|---|---|
| *Month* | Month related to the impact |
| *Municipality* | Location where the impact occurred |
| *MSSH* | Maximum hourly sea surface height in a day |
| *MWIH* | Maximum hourly significant wave height in a day |
| *WIH* | Daily average significant wave height |
| *PRCMAX* | Maximum hourly precipitation in a day |
| *PRCTOT* | Total daily precipitation |
| *PRCTOT_TOT_MAX_3* | Maximum daily total precipitation in the previous 3 days |
| *RX-1day* | Maximum daily precipitation in a month |
| *URmax* | Maximum hourly relative humidity in a day |
| *VRFDd* | Maximum hourly wind velocity in a day |

The indicators are not independent from one another, especially those describing the same phenomenon, hence there is a lot of redundancy in the information they provide. However, each indicator adds useful information to the analysis. The results of the hazard data analysis are presented in Section 3.4.2.

### *3.3.3. Development of machine learning algorithms*

AI and ML algorithms offer a new path to address the analysis of multiple environmental hazards due to their ability to model complex feedback and non-linear interactions between different factors without the need for an explicit modelling. In the frame of this work, several supervised ML methods for binary classification, whose goal is learning a function that maps input features to their associated classes (Goodfellow et al., 2016), were tested. During training, each of these algorithms takes as input

the values of the hazard-related indicators (e.g., the atmospheric and oceanographic indicators) and as output the corresponding value of the risk score, which, for labelled data, can only be 1 for samples associated with impacts and 0 otherwise. During testing and application, the outputs of the algorithms applied to new samples are the corresponding estimated risk scores.

*3.3.3.1. Performance metrics*

The following step of the ML design consists in the choice of the metric, which is a scalar function that takes as input the estimated and the observed output for the whole dataset and calculates the error, a single real number that describes the distance of the algorithm result from the target: the lower the error value, the better the algorithm performance (Figure 3). The metric is then used to optimize the values of the algorithm parameters and to compare the performances of different algorithms.

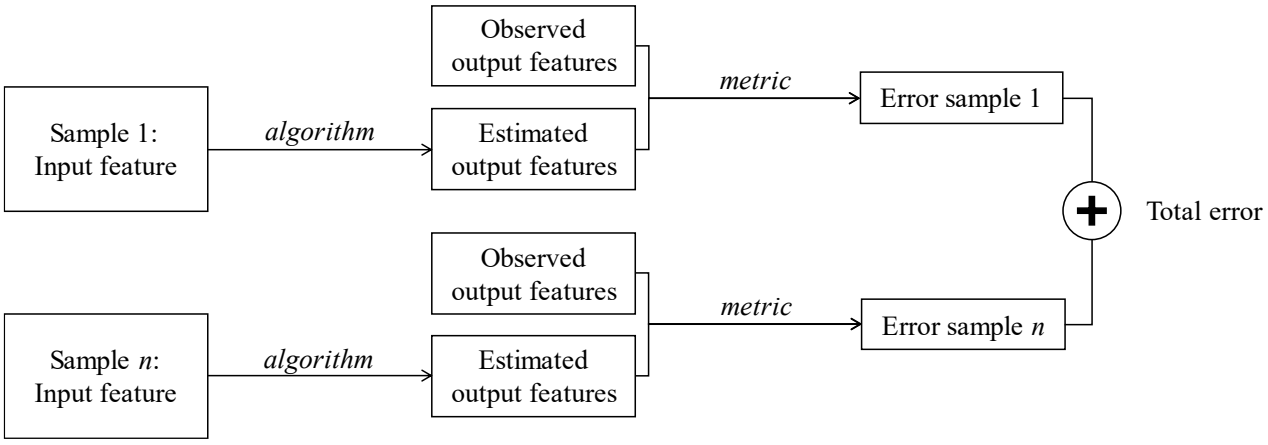



*Figure 3. Scheme of the calculation of the error for each algorithm: for each sample the algorithm calculates the estimated output features. The distance between the estimated and the observed output features for each sample is calculated by the metric, and the weighted sum of the sample error over the dataset represents the performance of the algorithm on the dataset.*

The choice of the metric is extremely important as it would set the objective of the analysis and defines which errors are worse than others, influencing the results more than any of the other choice. To define the metric for this specific case study (i.e., a binary classification problem of an extremely skewed dataset), we need to address two issues: *(i) how to calculate the error of each sample? (ii) which weight to attribute to each class?*

Considering the estimation of the error for a single sample first, most algorithms for binary classification (including the one implemented in this study) calculate a probability pi that a sample *i* is associated to the positive class. Consequently, it is possible to associate a sample *i* to the positive class if this estimate $p_i$ is above a threshold $T$ and to the negative class otherwise. A metric that estimates the error for each sample can be based on the difference between the observed and the estimated class label (Figure 4a), or on the difference between the observed class label and the

estimated probability value (Figure 4b). The main difference between these approaches is that, when using a metric based on the number of samples that fell into each class (e.g., accuracy, precision, recall, F1 score), the same loss can be attributed to events with very different values of risk score (points P1 and P2 in Figure 4a have the same loss, while their risk score is very different). On the other hand, if a metric such as the log-loss is used, two elements belonging to the same class but with different predicted probabilities have a different loss (points P1 and P2 in Figure 4b have the different losses).

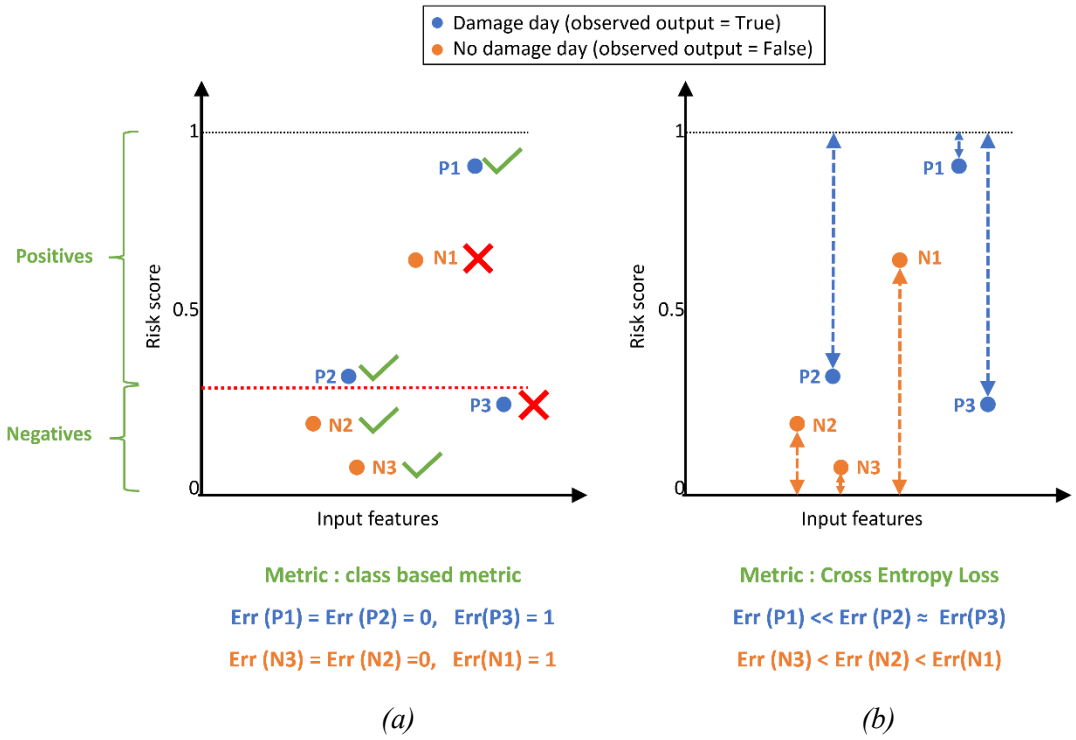



*Figure 4. Schematization of a class-based metric (a) versus a risk score-based metric (b). In (a) the risk score value estimated for each sample is only used to be compared against a threshold (red dotted line). All samples with risk score higher than the threshold are considered positives, and the others are considered negatives, irrespectively of the value of the risk score inside the range. In (b) the error of each sample is associated with the risk score value of the sample, and no threshold is considered.*

The risk score-based metric *'Cross Entropy Loss'* has been used because this function can better represent the uncertainty of the problem and allows for more flexibility in the use of the results. However, as the knowledge of the class (i.e., if a sample is likely associated to an impact) is useful in most applications, the weighted-F1 score is also used to analyse the results. The threshold is defined by maximizing the weighted-F1 score on the test dataset.

In rare event estimation most classification algorithms can sharply underestimate the probability events belonging to the minority class (King et al., 2001): possible solutions of the unbalance problem can be the application of weights, the under-sampling of the majority class or the oversampling of the minority one (Cahyana et al., 2019; Ertekin et al., 2007; He & Cheng, 2021).

In light of these considerations, the explicit formula of our chosen metric, the (binary) cross entropy with weights inversely proportional to the cardinality of each class, is:

$$loss = \frac{1}{n}\sum_{i=1}^{n} w\,[y_i\, ln\,(f(x_i))\,] + (1 - y_i)\, ln\,(1 - f(x_i))\,,$$

where $w$ is the ratio between the number of elements in the negative class and in the positive class and $f(x_i)$ is the predicted value of the risk score for sample $x_i$. It is important to note that the risk score calculated by the algorithm is not the probability of having an impact on a given day because the weights are not 1.

*3.3.3.2. Algorithm*

To design a ML model for the analysis of impacts related to atmospheric and marine hazards, the available data must be divided into training/validation and test sets. In this work, the data is split chronologically (Lam et al., 2022) – i.e., the train and validation dataset correspond to the years from 2009 to 2016, and test dataset corresponds to the years after 2016. This choice, although not ideal from a ML point of view, is justified by the non-independence of data samples: some indicators are monthly or yearly, and others are based on the values that the indicator assumed in the previous days, hence indicators of adjacent days are correlated.

Then, several ML algorithms were coded using *ScikitLean* (Pedregosa et al., 2011), trained, tuned and compared: (i) Multi-Layer Perceptron, which is a type of neural network (MLP henceforth; Murtagh, 1991), (ii) a Random Forest (RF henceforth; Breiman, 2001), and (iii) a Support Vector Classifier (SVC henceforth; Chang & Lin, 2001). Regularization coefficients were used in the MLP and SVC algorithms to reduce the risk of overfitting (Ying, 2019). Other options were also considered, including autoencoders (Baldi, 2012) and isolation forest (F. T. Liu et al., 2008) for anomaly detection, but as the preliminary results were not promising, these options were dropped in the early stages.

Given the relatively small amount of data available, to reduce the high redundancy of clusters of features (e.g., precipitation features, sea features) and the risk of overfitting, during the ML analysis the number of indicators were iteratively decreased, gradually removing the indicators that, accordingly to the feature importance, did not play a key role in the estimate of the result. After each step of this procedure, the algorithm performances were checked. Moreover, an error analysis was performed iteratively on the training set (Ng, 2021), and outliers were identified and cross-checked. The final parameters of the algorithms are listed in Table 3.

In order to increase the weight of positive events, oversampling of the minority class in the training dataset is performed before training. Oversampling was performed using the *SMOTE* tool implemented in the *imblearn* package (Chawla et al., 2002).

*Table 3. Parameters for the implemented ML algorithms – i.e., Multilayer Perceptron (MLP), Random Forest (RF) and Support Vector Classifier (SVC).*

| **RF** | | **MLP** | | **SVC** | |
|---|---|---|---|---|---|
| *Number of Trees* | 200 | *Maximum # of iterations* | 2000 | *Kernel* | rbf |
| *Max depth* | 4 | *n. hidden layers* | 2 | *C* | 0.01 |
| *Criterion* | Log Loss | *Hidden layer sizes* | 5 | *Probability* | True |
| *Minimum sample split* | 5 | *Alpha* | 3 | *Degree* | 3 |

The algorithms are then applied to the test dataset, and results are summarized in the Section 4.2.

#### *3.3.3.3. Feature importance for sensitivity evaluation*

A sensitivity analysis was performed to identify the most influential factors in the impact generation, which is important for the impact prevention and management. This sensitivity analysis was carried out using the permutation method for the estimation of the feature importance, which was defined by Breiman (2001) as the decrease of the metric value when the values of a single feature are randomly shuffled. Features are important if they contain valuable information, hence the more important a feature is, the more the prediction results will be affected by its incorrect values; this decrease of performances may be a measure of the importance of that specific feature.

The implementation of the method consists of randomizing one input feature at a time, calculating the corresponding metric value and repeating the process several times to reduce the sensitivity to the randomized set.

The contribution of the atmospheric, oceanographic, temporal, and geographical factors to impacts was explored. In addition, to better understand the contribution of exposure and vulnerability to the dynamics of risks, the feature importance was performed on groups of municipalities sharing similar patterns, as detailed in Section 3.3.3.3. The results of these analyses are illustrated in Section 3.4.3.2.

## 3.4. Results

As described in Section 3.3, the proposed study was organized into a preliminary data analysis and the following implementation of the ML algorithms. Specifically, the results of the exposure and vulnerability analysis are presented in Section 3.4.1, whereas Section 3.4.2 highlights the outcomes

of the conditional distribution of the input data for the algorithm. Finally, Section 3.4.3 outlines the result of the ML model application along the coastal municipalities of the Veneto region, as well as the results of the feature importance for the whole Veneto region and the group of municipalities.

### *3.4.1. Exposure and vulnerability results*

Exposure and vulnerability factors have been analysed to outline the territorial characteristics of the investigated case study, which may intensify the effects of extreme weather events.

The coastal municipalities of the Veneto region have been divided into four groups which share similar features (Figure 5). The main criteria used to create these groups are the geographical position and geomorphology.

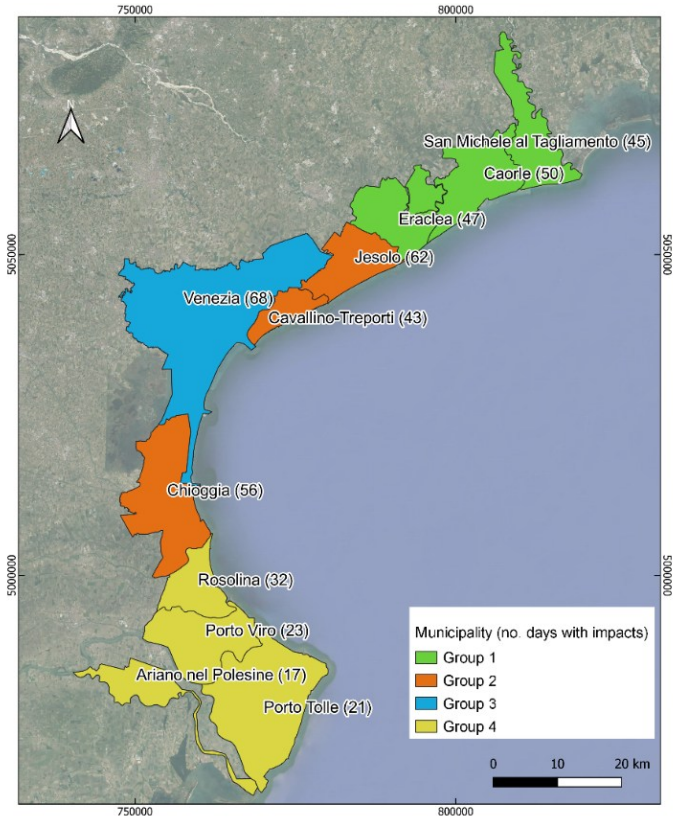



*Figure 5. Classification of the coastal municipalities according to the occurrence of the impacts, as well as on the characteristics of exposure and vulnerability.*

The municipalities belonging to each group are adjacent to each other; the only exception is the municipality of Venice, which was extracted from Group 2 due to its peculiar vulnerabilities related to its cultural heritage and to its high population density (Figure 6). Municipalities belonging to the same group share the same orientation and similar geomorphological characteristics (e.g., river valley, lagoon, river delta; Figure 6). It can be noted that municipalities in each group are also affected by similar number of impacts.

The resulting outputs of the data analysis for each group of municipalities are shown in Figure 6, and the characteristics of each group are described below, from North to South.

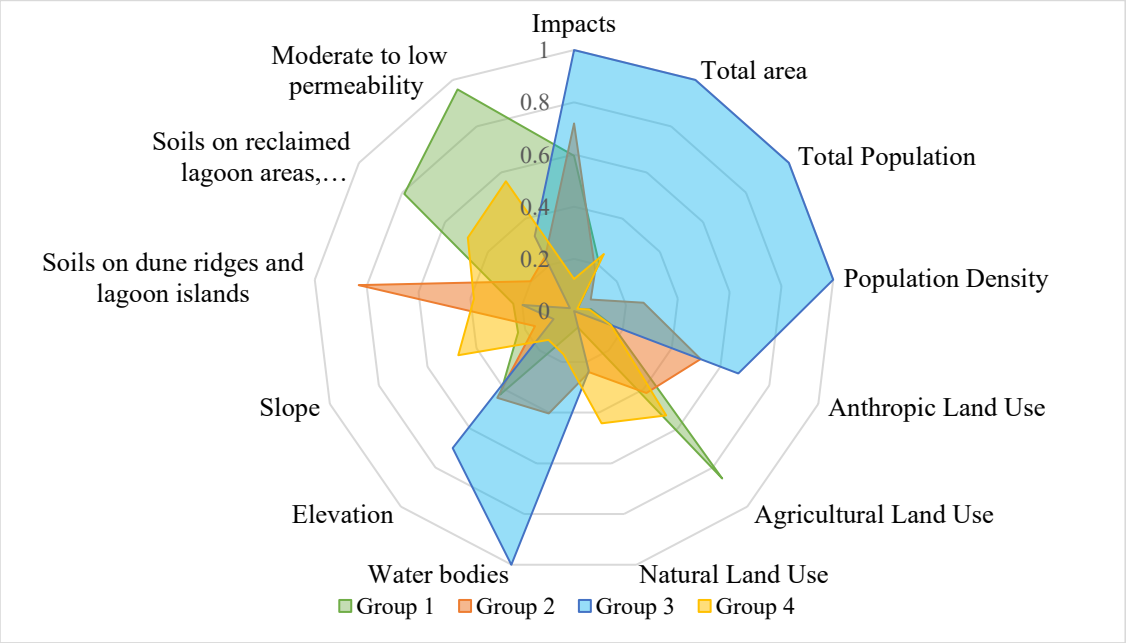



*Figure 6. Visualisation of the analysis combining the historical impacts and territorial features carried out to characterise the coastal municipalities of the Veneto region.*

*Group 1* consists of the municipalities of San Michele al Tagliamento, Caorle and Eraclea. The territory is mainly covered by agricultural fields, which are former lagoon areas that have been reclaimed and artificially drained, lowering the soil permeability coefficient.

The lagoonal municipalities of Jesolo, Cavallino-Treporti and Chioggia have been assembled in *Group 2*. Although the dunes have been reinforced to protect the mainland in all these municipalities, this group has the second highest number of impacts. However, the high number of impacts may be due the presence of tourist facilities that increases the exposure of the area. The municipality of Venice, identified as *Group 3*, is by far the biggest, the most densely populated and urbanised municipality, covering the highest extension of water (i.e., lagoon and coast), which increases the inundation risks. It has recorded the most impacts, probably because of its size, population and high vulnerability, especially related to its historic centre, classified as UNESCO World Heritage site. Accordingly, due to its peculiarity, the municipality of Venice forms a group by itself.

Finally, the municipalities located in the province of Rovigo (i.e., Rosolina, Porto Viro, Porto Tolle and Ariano nel Polesine – *Group 4*) are the least developed, and the area is covered by rural fields and natural parks (e.g., River Po Delta Regional Park).

### *3.4.2. Hazard data analysis results*

In order to understand the relationships between hazards and impacts, the conditional distribution of each hazard when an impact and when no impact is recorded are analysed (Figure 7).

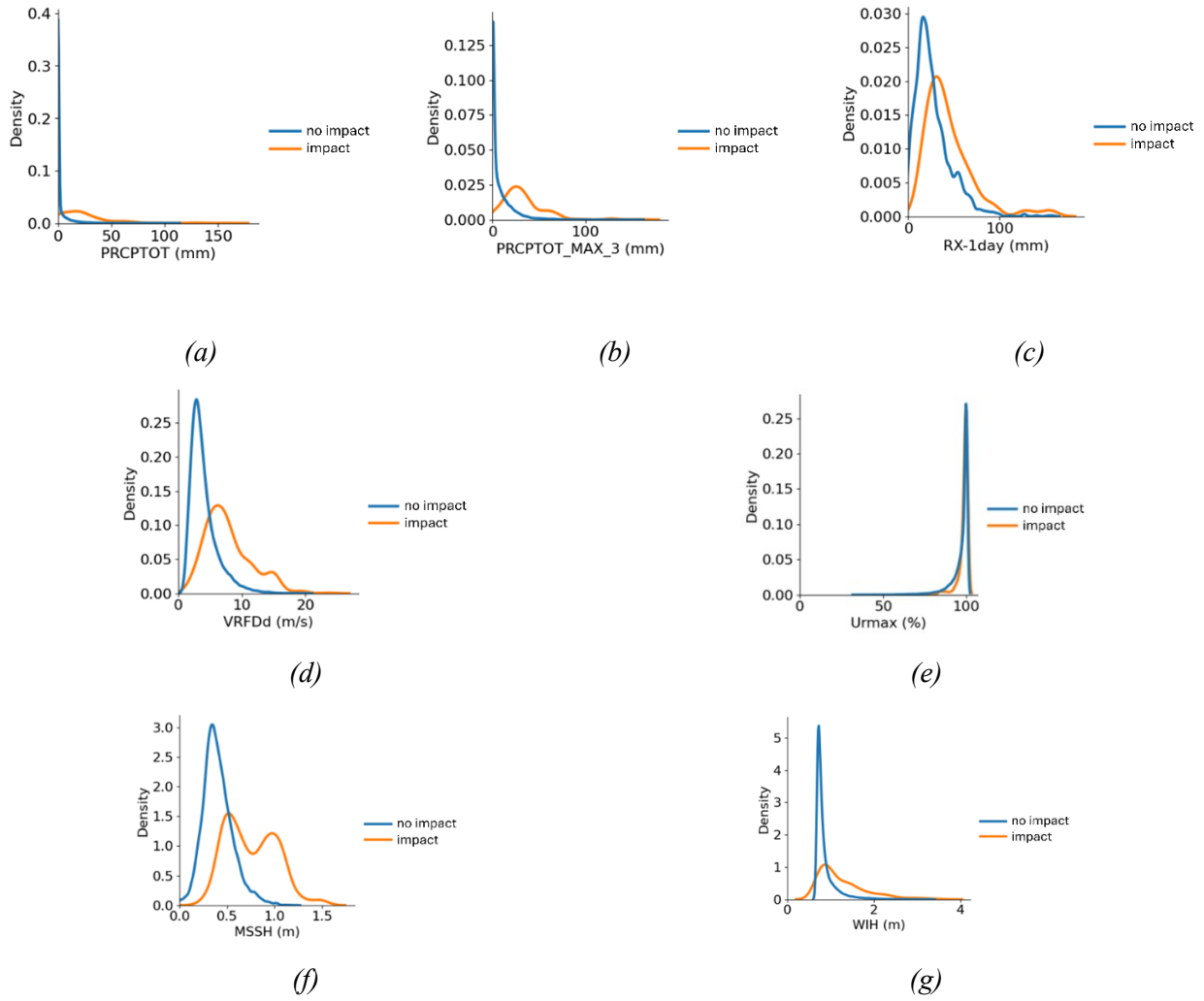



*Figure 7. Distribution of the indicators (introduced in Table 2) of samples with and without impacts: the blue curves represent the distribution of hazards in samples with no impact recorded, while the orange curves represent the distribution of hazards in samples with impact recorded.*

The indicators related to precipitation (i.e., PRCTOT, PRCMAX, PRCTOT_TOT_MAX_3, and RX-1day), sea surface height (MSSH), wave height (MWIH and WIH) and wind velocity (VRFDd) show that the orange curve has a higher average and variance than the blue one. This means that impacts are more likely to occur if the values of precipitation, sea surface height, wave height or wind velocity are higher, as expected. However, for most indicators the range of values in which the distribution overlap is quite wide, indicating that a single feature analysis would not be enough to estimate the presence of an impact, hence suggesting the need to multi-features approaches (e.g., ML). On the other hand, the difference in the distribution of maximum humidity over the previous 3 days (URmax) is more subtle, suggesting that this indicator is not strongly correlated with the presence of impacts.

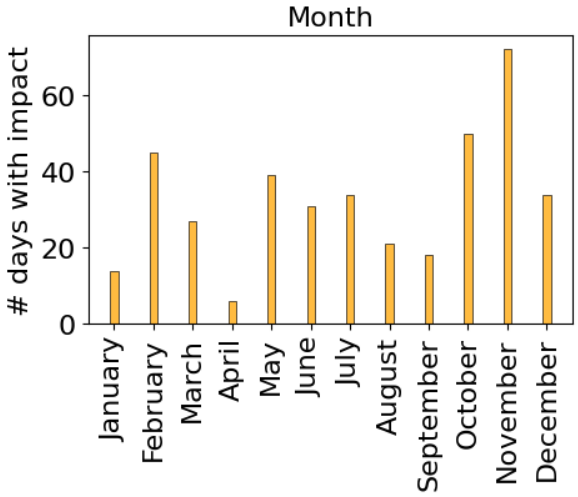



*Figure 8. Histogram representing the number samples associated with impacts per calendar month during the 2009-2019 timeframe.*

Finally, the histogram in Figure 8 shows three peaks of recorded impacts throughout the year. In particular, the highest values belong to the autumn months (i.e., October and November), followed by February, and the months with increasing heat (i.e., May, June, and July).
This result suggests that the month indicator has meaningful relevance for machine learning models.

### *3.4.3. Machine learning results*

In this section, the results of the application of the ML algorithms and the corresponding feature importance are illustrated. In Section 3.4.3.1 the results of the binary classification are shown. The goal of this paragraph is to show that the algorithms work properly, and hence can be used to estimate the risk score of new data. Section 3.4.3.2 on the other hand describes the feature importance obtained by the application of the best performing algorithm, with the aim of understanding the phenomena that generates the occurrence of impacts in different areas of the Veneto coast.

#### *3.4.3.1. Classification results*

The objective of the ML application is the estimate of a risk score for each sample; the risk score is calculated by the implemented ML algorithms using the climate-relate hazard indicators (i.e., atmospheric, and marine drivers of impact) as inputs.
The results obtained by the three algorithms are shown in Figure 9, where each point corresponds to a sample in the input data (i.e., a couple of date and municipality). In particular, blue points represent the samples associated to an impact and orange points samples associated to no impact. The vertical position of the point represents the risk score: if a point has a high risk-score, it is more likely to be affected by an impact.

In the training process, each algorithm determines its parameter by minimizing the error between the calculated and the measured outcome (i.e., by trying to move all the blue points to the top of the plot, and all the orange points to the bottom), while in the testing phase the information on the impact is only used to measure the quality of the results. Ideally, blue points in both training and in testing should be placed as close as possible to 1 and all orange points to 0. The results of Support Vector Classifier (SVC) and Multi-Layer Perceptron (MLP) are quite similar, with most orange points very close to 0 and most blue points on the upper side of the plot. Compared to these algorithms, in the Random Forest (RF) results the separation between blue and orange points is less sharp.

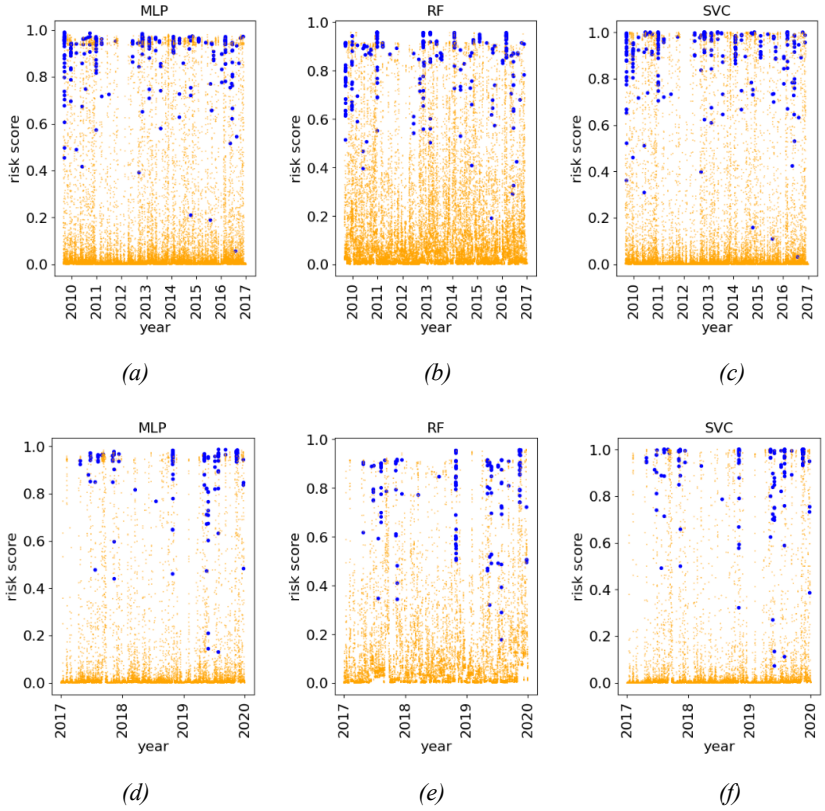



*Figure 9. Predicted risk score on the train dataset for MLP (a), RF (b), SVC (c) algorithms and predicted risk score on the test dataset for MLP (d), RF (e), SVC (f) algorithms. Blue point represents samples associated with impacts, and orange point represents samples not associated with impacts.*

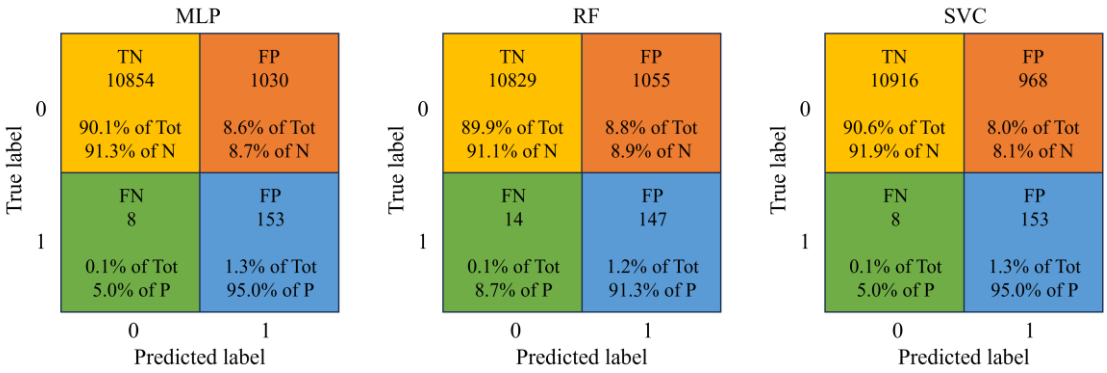
The calculated weighted log losses for the train and test dataset respectively are 0.33 and 0.4 for the MLP algorithm, 0.42 and 0.59 for the RF, 0.36 and 0.45 for SVC. As the quality of the results is similar between the training and the test, the algorithm is not overfitting the data.

For some applications (e.g., early warning systems) it may be useful to decide, based on the value of the risk score, if the sample is at high risk of impact or not. To do that, we need to set a threshold, such that all the samples that have a risk score higher than this value is considered at high risk, while samples with a risk score lower than this threshold are not. The value of this threshold can be chosen by the end-user. If a conservative measure is needed (i.e., if it is important to flag every sample that

can be reasonably associated to an impact) a low value for the threshold will be chosen. The drawback of this choice will be a high number of false positives (i.e., samples flagged as high risk that did not present any impact). On the other hand, if some false negatives are acceptable (i.e., days not flagged as high risk that were eventually affected by an impact), the number of false positives can be reduced. In the frame of this study a threshold was selected by maximizing the value of the weighted F1 score of the MLP algorithm, which is a standard metric used on binary classification. The weighted F1 score is maximum and presents a plateau between 0.4 and 0.6, i.e., its value is almost constant for this range of threshold values. The value of 0.5 was set as threshold, as it is located in the middle of the plateau.

The confusion matrix, calculated using the threshold of 0.5 on the test dataset (Figure 10), illustrates the performances of the algorithms. The confusion matrix describes how the samples are divided between True Negatives (samples correctly labelled as low risk), False Positives (samples incorrectly labelled as high risk). False Negatives (samples incorrectly labelled as high risk), True Positives (samples correctly labelled as high risk). In each box the total number of samples of the test set that fell in each category is reported, together with the percentage of samples over the total number of samples, and the percentage of samples over the total samples with the same true label.

As a result, MLP and SVC algorithms shows only 8 False Negatives from a total of 161 days with impacts, against the 14 False Negatives detected by RF. Moreover, all algorithms incorrectly label approximately 9% of negative samples as high risk (False Positives), and between 5 and 9% of positive samples as low risk.




*(a)* *(b)* *(c)*

*Figure 10. Confusion matrix for a threshold of 0.5 for MLP (a), RF (b), SVC (c) algorithms. In each confusion matrix the top left square (true label = 0, predicted label = 0) contains the number of True Negatives (TN). The top right square (true label = 0, predicted label = 1) contains the number of False Positives (FP). The bottom left square (true label = 1, predicted label = 0) contains the number of False Negatives (FN). Finally, the bottom right square (true label = 1, predicted label = 1) contains the number of True Positives (TP). In each square it is reported the total number of samples that fell in the corresponding category, the percentage of samples over the total number of samples (Tot), and the percentage of samples over the total samples with the same true label (i.e., N for negative samples, and P for positive samples, respectively).*

*Table 4. Test set metrics for the implemented ML algorithms – i.e., Multilayer Perceptron (MLP), Random Forest (RF) and Support Vector Classifier (SVC).*

| | **Not weighted metrics** | | | | **Weighted metrics** | | | |
|---|---|---|---|---|---|---|---|---|
| | **Precision** | **Recall** | **F1 score** | **Accuracy** | **Weighted Precision** | **Weighted Recall** | **Weighted F1 score** | **Weighted accuracy** |
| *MLP* | 0.13 | 0.95 | 0.23 | 0.91 | 0.94 | 0.95 | 0.94 | 0.93 |
| *RF* | 0.12 | 0.91 | 0.22 | 0.91 | 0.93 | 0.91 | 0.92 | 0.91 |
| *SVC* | 0.14 | 0.95 | 0.24 | 0.92 | 0.94 | 0.95 | 0.95 | 0.94 |

Table *4* summarizes the values of the classic metrics obtained on the test set of the threshold of 0.5. The first columns report the values of the non-weighted metrics, where the importance of positive and negative samples in the calculation is the same; as expected, the precision, and consequently the F1 score calculated are small, due to the huge number of false positives previously discussed. In the second half of the table, the values of weighted metrics, calculated by weighting each sample with a weight inversely proportional to the cardinality of its class (calculated on the test set), show satisfactory results for all the metrics. The difference between weighted and non-weighted values of precision and F1 score is due to the skewness of the input data, and to the choice of giving more importance to positive samples, as they are outnumbered by the negative samples. The use of weighted metrics is more coherent with the choice of the loss function described in Section 3.3.3.1 and with the goal of the application.

These results confirm a similar good performance for SVC and MLP, and a slightly worse performance of RF.

In terms of computational cost, the three algorithms show very different performances. To train the algorithm the MLP algorithm takes 6s, the RF algorithm takes 12s, and the SVC algorithm takes 289s on a laptop computer (processor: Intel(R) Core(TM) i7-10875H CPU @ 2.30GHz 2.30 GHz; RAM 160GB). It must be noted, however, that computational cost was not an issue given, and no effort was devoted to reducing it, or to find faster implementations of the routines, and the computational cost are here reported for completeness, without the assumption that these considerations can be generalised.

#### *3.4.3.2. Feature importance*

The feature importance, introduced in Section 3.3.3.3, is aimed at identifying the variables that influence the occurrence of impacts along the coastal municipalities of the Veneto region. It consists in calculating the metric function when a feature is randomly shuffled: the more the value of the

metric increases, the more important the shuffled feature is. It can consider as a sensitivity analysis, as it evaluates the impact that the correct value of each parameter has on the quality of the result.

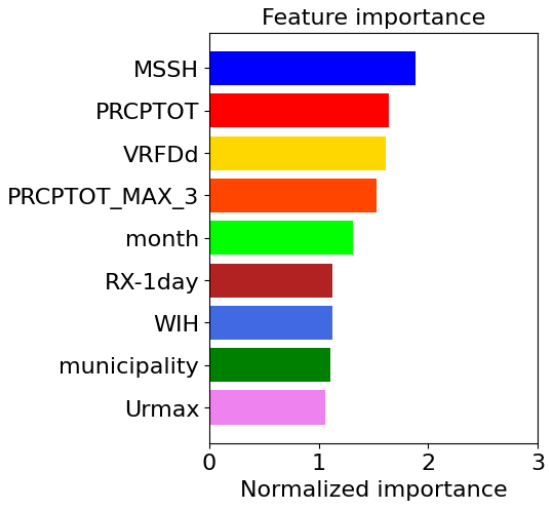
In Section 3.4.3.1 it was shown that SVC and MLP algorithms produced similar results (with the MLP algorithm being more computational effective) which outperformed the RF algorithm. For this reason, of the three ML algorithms trained, validated and tested (i.e., RF, SVC, and MLP) within the 2010-2019 timeframe, only the results for the MLP algorithm are shown in Figure 11a.

The most important factors triggering impacts in the investigated case study are indicators of maximum sea surface height (i.e., MSSH), total precipitation (i.e., PRCPTOT), and wind intensity (i.e., VRFDd). These results agree with the analysis of conditional distributions, detailed in Figure 7. In particular, Bora and Sirocco wind jets expose the coastal area of the Veneto region to strong winds, heavy rainfall, strong sea storms and flooding, of low frequency but extremely intense (Stocchi & Davolio, 2017). Moreover, the presence of several indicators of precipitation leads to a high level of redundancy, thus reducing the importance of each feature. If a feature shows different conditional distributions according to the presence or absence of impacts, the same feature will have high importance in the corresponding machine learning algorithm.

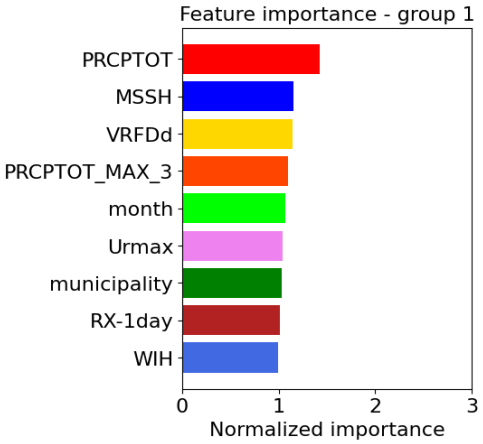
Furthermore, in accordance with the characterization of the coastal municipalities presented in Section 3.4.1, the feature importance for each cluster of municipalities has been calculated to understand how exposure and vulnerability play a key role in determining the drivers of impacts.

In Group 1, composed of the coastal municipalities of San Michele al Tagliamento, Caorle and Eraclea, the main driver of impact is the total precipitation, which dominates the importance ranking, as shown in Figure 11b. This behaviour is corroborated by (Stocchi & Davolio, 2017) where several extreme events occurred in the area have been analysed. The study highlights how summer and autumn seasons are characterized by marked convective activities, with precipitation systems also affecting the lowland area that faces the Adriatic coast. As described in Figure 6, the low permeability that characterizes the soil of these municipalities could exacerbate the effects of the precipitations, hence contributing to the occurrence of impacts.

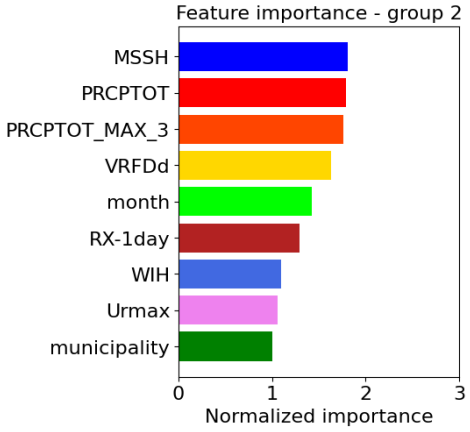
Group 2 (i.e., Jesolo, Cavallino-Treporti and Chioggia) and Venice (Group 3) present the highest number of impacts, possibly because of the size (Venice) and of the high percentage of anthropic land use in both groups (Figure 6). The impacts are mainly governed by extreme sea-level related events (Figure 11c and Figure 11d). These phenomena are exacerbated by the combined effect of sea-level rise and subsidence (Lionello et al., 2020), that makes these areas more impacted (as detailed in Section 3.4.1). Besides that, although Group 2 is influenced by the intense precipitation coming from North (as seen for Group 1), Venice is famously affected by winds (i.e., Bora and Scirocco) which represents the major cause of Acqua Alta (i.e., high tide).



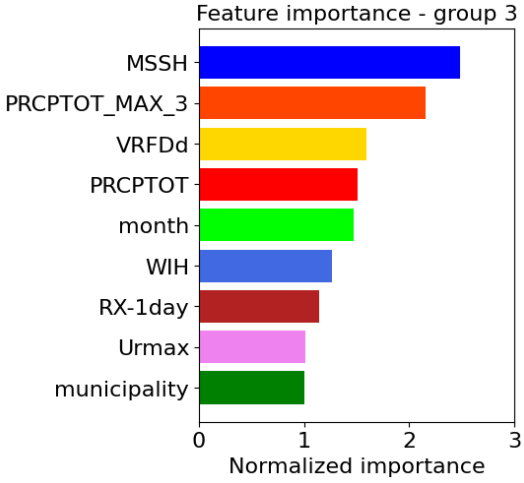

*(a)*



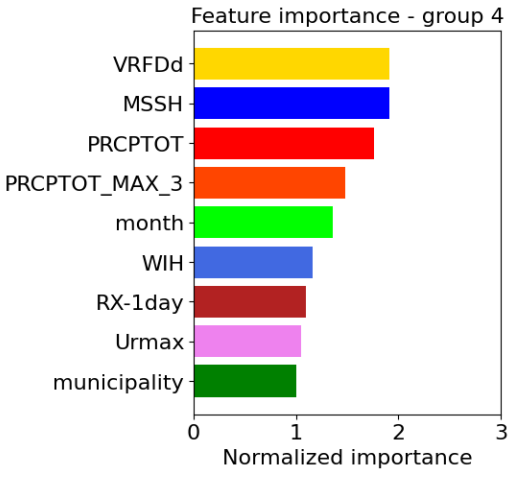

*(b)*




*(c)*




*(d)*




*(e)*

*Figure 11. Feature importance obtained for the whole Veneto coastal area (a) and for each group of municipalities: (b) is related to Group 1, which includes San Michele al Tagliamento, Caorle and Eraclea; (c) Group 2 covers the lagoonal municipalities of Jesolo, Cavallino-Treporti and Chioggia; (d) Group 3 is entirely devoted to Venice; and Group 4 represented in (e) contain the Rovigo municipalities of Rosolina, Porto Vito, Porto Tolle and Ariano nel Polesine.*

Finally, impacts recorded in Group 4 (i.e., Rosolina, Porto Viro, Porto Tolle and Ariano nel Polesine) are equally triggered by winds and sea-level related events (Figure 11e). These, together with the low elevation of the area (Figure 6), have historically made the river Po Delta area a famous hotspot for saltwater intrusion, especially during dry seasons, exposing the vast cultivated fields (Tarolli et al., 2023). However, the importance of sea-level and precipitation is lower compared to the previous groups of municipalities due to the limited availability of impact data (as discussed in Section 3.2.3), as the impact dataset is constrained by the 'Stato di crisi' records reported by the Veneto region. This outcome may be biased by the low rate of urbanisation and population density, hence by the low vulnerability, of the municipalities included in Group 4 (described in Section 3.4.1): the low vulnerability of these municipalities leads to only the most serious hazards being recorded to the exclusion of less serious ones. As it is very likely that most severe hazards are characterised by the compounding presence of precipitation, storm surge and wind, it is reasonable to expect that the feature importance of these indicators are similar.

## 3.5. Discussion

The study was developed to create an algorithm able to estimate, given a set of environmental indicators, a daily risk score for each coastal municipality of the Veneto region, and to understand the extreme events that caused the occurrence of impacts, through the analysis of feature importance in the reference timeframe (2009-2019).

Compared with other available decision support systems for climate change adaptation in coastal areas (e.g., DSS-DESYCO and THESUS; Torresan et al., 2016; Zanuttigh et al., 2014), the novelty of the Machine Learning (ML) model developed within this application is that, to the authors' knowledge, for the first time Artificial Intelligence (AI) methodologies are used to estimate the risks as a result of extreme weather events, along the coastal municipalities of the Veneto region. Furthermore, although the algorithms developed for this application are simple, the study offers insight into how ML models can be employed for environmental and multi-risk assessment under climate change. Therefore, the developed model represents an early prototype decision support tool underpinning climate change risk assessment and the definition of adaptation strategies at the regional scale.

After a preliminary analysis of the input dataset, several ML strategies for the estimation of the daily risk score have been considered: the SVC and the MLP algorithms provided similar results, which were satisfactory in terms of performances and excluded the risk of overfitting, meaning that the developed tools are reliable and ready to be used.

The MLP algorithm was used to calculate the relative importance that each type of hazard plays in the creation of impacts (i.e., feature importance). This analysis was performed also per group of municipalities, highlighting how the vulnerability and exposure characteristics of each group can amplify or mitigate the occurrence of impacts. This analysis shows that southern coastal areas (i.e., province of Rovigo), characterized by a larger natural area, experienced less impacts, whereas more urbanized and more densely populated municipalities (e.g., Venice, Jesolo, Chioggia) were the most affected.

One of the challenges of the implementation of the ML algorithm was the skewness of the input dataset: most input samples are associated with a negative label, while approximately 1% of the samples are associated to a positive label. The skewness of the data is a very common issue in several science fields (Maalouf & Trafalis, 2011), and it is almost always addressed using weights or oversampling in the training, validation, and testing phase, and in the definition of the loss function and the metric. In this work the same strategy has been applied. Drawbacks of this choice are the high number of false positives in the results; the advantage, on the other hand, is the ability to keep the minority class in the right account, which is of course the main priority of the work. Several binary classification metrics were used to analyse the results: non-weighted metrics such as precision and F1 score are strongly influenced by the high number of false positives, while weighted metrics are not. This result is not ideal, but this problem is intrinsic in all binary classification problems on skewed dataset. It is important to understand the meaning of these results: even if the risk score of a sample assumes a high value, there is the possibility that no impact would occur on that day, i.e. that the sample is a false positive. Stakeholders and local administrations that would like to use the results or the algorithm for adaptation and mitigation planning should be aware of this limitation.

Even if the first results obtained applying the ML model for the coastal area of the Veneto region are promising, some improvements could be achieved with the use of a more detailed impact dataset: since the preliminary data analysis, it was clear that the main limitation of this study is the scarcity and low accuracy of the impact dataset: this issue is critical, as the results of any machine learning tool are at best as good as the input data. The impact list retrieved from the 'Stato di crisi' reports from Civil Protection, and cross-checked and integrated with analysis of local newspapers still presents some main problematics: namely incompleteness and inaccuracy (it is possible that some impacts are not present), lack of the number of events per municipality on a given date, lack of economical information on the impact, lack of typology of the impact, lack of the precise location, and hence vulnerability and exposure, of the target.

In order to partially overcome these issues, a robust procedure that includes the use of simple algorithms, feature analysis, a manual analysis of the outliers, an error analysis on the train set, and

the use of regularization coefficients to reduce the risk of overfitting was implemented. However, it is important to remember that no processing techniques can make up for the low data quality.

Much more meaningful results could have been achieved with very similar algorithms with more impact information available. If the entity of the impacts (like the economic loss), or at least the number of impacts on a given day in each municipality were available, it would be possible to normalize the impacts over the municipality size or the population. The actual impossibility of normalizing the impacts has a major consequence on the analysis, as any measure of the contribution of the municipality, with its exposure and vulnerability characteristics, in the determination of impacts, concludes that bigger and more populated municipalities are more affected. If detailed information on the impact were available (e.g., location, entity, type of impact, magnitude, information on the structure/activity affected by the impact), local exposure and vulnerability factors could be considered in the analysis: geographic, hydrographic and geological information, on local or municipality level, together with infrastructural networks maps, will also be included in the analysis as indicators. Similarly, socioeconomic dynamics (e.g., urbanization, population growth, migrations, tourism, economical activities) could be integrated to consider the effect of their interaction with climatic drivers in exacerbating the risk and vulnerability towards disasters. Moreover, if the characteristics of the impacts would be known, the plethora of assessment endpoints could be extended, including different types of damages (e.g., structural damage, flood damage, water quality alteration, infrastructure disruption).

For these considerations, it is strongly recommended that local authorities and the scientific community would cooperate for the creation of a standardised impact dataset. The existence of such a dataset would improve massively the quality of multi-risk studies and would help the scientific communities to share their know-how.

The same algorithm can be applied to other geographic areas, with the same or different indicators and assessment endpoints, provided that the algorithm is retrained or fine-tuned on local data.

This tool is also meant to be the first step of a methodology for the estimation of the number of impacts per year over the Veneto coastal area, which will be applied to modelled future projections of marine and atmospheric indicators to estimate the impact of climate change in future timeframes.

Future development of the methodology may include the implementation of ML tools such as Recurrent Neural Networks or Graph neural networks, which would be able to take into account spatial and temporal dependencies in the analysis. The development of the algorithm followed the guidelines for robustness and explainability of artificial intelligence developed by JRC (Hamon et al., 2020): the developed algorithm is robust, as it has been tested on new data to avoid the risk of overfitting; results are reproducible, as it has been built in an ad hoc environment and any random

seed is hardcoded, and it is transparent, as mainly python libraries are used, and all the parameters are summarized in this paper. The algorithm is also explainable, as a function that calculates the feature importance has been implemented. No sensitive data has been used to train and test the algorithm. The algorithm is not developed to take autonomous decisions that would affect people's lives, but it has been designed to be used by researchers and local authorities as an instrument able to increase the understanding of the phenomena underlying the occurrence of impacts in different area of the Veneto coast, and hence helping the mitigation planning process. It can also be used as an early warning system when applied to short term weather forecasts. It is recommended to retrain or fine tune the algorithm regularly with new data, to consider changes in the dynamics, or new mitigation structures in place.

# Chapter 4. *Second paper*[13]

# Integrating AI and climate change scenarios for multi-risk assessment in the coastal municipalities of the Veneto region

**Abstract.** Global climate is experiencing exceptional warming, leading to a rise in extreme events worldwide. Coastal regions are particularly vulnerable to climate change (CC), due to dense populations, interconnected economies, and fragile ecosystems. These areas face escalating risks as CC intensifies the severity and frequency of extreme weather phenomena, like heavy precipitation, sea-level rise (SLR), storm surges.

Integrated approaches are crucial to assess the combined impacts of atmospheric and marine hazards at the land-sea interface. Machine Learning (ML) offer innovative solutions to analyse multi-risk events, leveraging large and heterogeneous datasets and modelling complex, non-linear interactions.

This study introduces a two-tier ML approach to estimate risks associated with extreme weather events for the Veneto coastal municipalities under current and future scenarios. The model, tested and validated with present-day data, showed satisfactory performance (error margin ~20%). The model was applied to mid-term (until 2045) and long-term (until 2100) periods under different CC scenarios, represented by various Representative Concentration Pathways (RCP). Mid-term analysis reveals an increasing risk trend, driven by SLR under RCP8.5, underscoring the significance of considering non-linear interactions between multiple marine and atmospheric hazards. Long-term analysis highlights how future risks depend mainly on precipitation and SLR across the analysed CC scenarios (RCP2.6/4.5/8.5). Results indicate a gradual increase in the expected annual risk trend, with RCP8.5 scenario showing the most severe outcomes. By 2100, the risks under RCP8.5 are projected to be ten times higher than those observed during the historical period, highlighting the importance of developing effective strategies to address these challenges.

[13] This Chapter is derived from Dal Barco et al., 2025: "Integrating AI and climate change scenarios for multi-risk assessment in the coastal municipalities of the Veneto region", published in *Science of the Total Environment*, Volume 965, February 2025, 178586. https://doi.org/10.1016/j.scitotenv.2025.178586.

## 4.1. Introduction

Over the past three decades, global temperatures have soared to unprecedented levels, driving a significant increase in frequency and intensity of extreme events worldwide (IPCC, 2023). Coastal regions are particularly vulnerable to these climate-change-induced impacts due to the combination of high population density, interconnected economic activities, fragile ecosystems, and the complex interactions of multiple hazards occurring across varying temporal and spatial scales. Among these, rising sea surface temperatures, a direct consequence of climate change, have played a pivotal role in amplifying the severity of these extreme events.

In the Atlantic, hurricanes have become increasingly frequent and intense, with devastating consequences for coastal communities (Méndez-Tejeda & Hernández-Ayala, 2023; Moharana & Swain, 2023). Hurricane Katrina in 2005 highlighted the catastrophic socio-economic and environmental consequences of such events (Diaz et al., 2020; Raker & Woods, 2023). It caused massive economic losses and became one of the deadliest disasters in recent history, underscoring the far-reaching consequences of climate-induced hazards (Diaz et al., 2020; Shek-Noble, 2023). Similar patterns are emerging in Europe, where the increasing occurrence of extreme marine and weather events is a growing concern (Weilnhammer et al., 2021). For instance, in 2018, Storm Adrian caused extensive damages across the Alpine region before reaching the Adriatic Sea a couple of days later, demonstrating the transboundary nature of such events (Biolchi et al., 2019; Menegatto et al., 2024). More recently, the Storm Dana in autumn 2024 caused extraordinary devastation in the Valencian coastal community, resulting in severe damage, significant loss of life, and exposing critical gaps in disaster management systems[14]. These events, driven by both marine and atmospheric hazards, marked a turning point highlighting the urgent need for a multi-hazard approach to achieve effective risk assessment and management (Hochrainer-Stigler et al., 2023; Ward et al., 2022). This approach is essential to address the escalating threats that vulnerable coastal regions are facing. Accordingly, an integrated approach is crucial to assess the interplay among all interacting risk factors (i.e., hazard, exposure, and vulnerability), as well as to evaluate the impacts that may occur at the land-sea interface. Recently, Artificial Intelligence (AI), particularly Machine Learning (ML) algorithms, has gained significant traction, offering a new path to tackle the analysis of these multi-risk events. These algorithms excel at integrating great volumes of heterogeneous data and modelling non-linear relations between multiple factors. The growing potential of data-driven methodologies is poised to transform climate risk assessment (Kashinath at al., 2021; Reichstein et al., 2019; Zennaro

[14] Spain floods: Death toll rises to 205 as nation braces for more rain – Kieran Guilbert for Euronews (31/10/2024): https://www.euronews.com/2024/10/31/several-missing-in-spain-after-heavy-rain-causes-flooding.

et al., 2021). By integrating diverse sources of information, ML approaches provide an unprecedented opportunity to capture complex multi-hazard interactions and evaluate their broader impacts on social, economic, and natural systems (Reichstein et al., 2019). For example, ML models have been widely used in studies analysing environmental-health risks, such as the combined effects of heat and air quality stressors (Boudreault at al., 2023; Guo et al., 2024; Wang et al., 2019). Similarly, population displacement has been studied through ML algorithms that investigate the dynamic relationships between droughts, conflicts, and food security (Tárraga et al., 2024). Additionally, significant progress has been made in developing innovative models to generate climate simulations at different spatio-temporal scales (Gualdi et al., 2013), and to assess the physical impacts of climate change (Park & Lee, 2020a; Pham et al., 2023; Saha et al., 2021; Sarhadi et al., 2017). To the best of authors knowledge, impacts have been modelled at global, regional and local scales worldwide (Tabari & Willems, 2023; Wang & Yan, 2021; Park & Lee, 2020). However, there remains a significant gap in multi-risk assessment at the local scale for the Veneto coast. While individual coastal risks, such as coastal erosion and water quality degradation, have been extensively studied and analysed (Dal Barco et al., 2024; Fogarin et al., 2023; Pham et al., 2023, 2024), no comprehensive studies have been conducted to address the combined risks in this region. This gap is particularly evident in the North Adriatic region, characterised by complex interactions among various hazardous events (e.g., sea-level rise, extreme precipitations, storms). Despite Dal Barco et al. (2024) analysed risks in the coastal municipalities of the Veneto region during the 2009-2020 timeframe, no studies have yet estimated the cumulative impacts of climate change starting from daily values of hazard indicators, or projected future trends in impact occurrence.

Building upon the gaps, this paper introduces a novel two-tier ML approach designed to estimate the annual occurrence of impacts in the Veneto coastal area, and the subsequent application of the developed algorithm to future climate change scenarios.

The aim of the methodology is the calculation of risk as the number of days in which at least an impact caused by extreme weather events occurs in the Veneto coastal area at municipality level. Although the application of binary classification algorithms for the identification of rare events is common to several subjects areas (Malik & Ozturk, 2020), such as weather predictions (de Coste et al., 2022; Rao et al., 2020), social science (Hain & Jurowetzki, 2020), political science (Hegelich, 2016), finance (Coffinet and Kien, 2019), manufacturing failure (Dogan & Birant, 2021), fraud detection (Yousefi et al., 2019), and medical examinations (Luca et al., 2014), the following step - i.e., estimation of the cumulative number of these events - is never discussed. The calculation of the cumulative value is a challenging task due to the skewness of the input dataset (i.e., the small number of days with impacts over the total number of days) that characterises rare events identification

problems (Z. Liu & Bondell, 2019). In the frame of this application, building upon the work discussed in Dal Barco et al. (2024), a multilayer perceptron (MLP) algorithm with weighted cross-entropy loss has been implemented to determine the daily risk score for each municipality, hence quantifying the likelihood of an impact to occur at the given location and day. This daily risk score is then used to estimate the annual frequency of days on which at least one impact is expected along the coastal municipalities. The algorithms were then implemented, trained, validated and tested on reanalysis data.

The algorithm was then applied to climate change scenarios, in order to evaluate the contribution of different hazards, the non-linearity effects, and to estimate how climate change will influence the impact frequency in the Veneto coastal area in the years to come.

Following the collection of the available data for the Veneto pilot is detailed in Section 4.2, highlighting the different models used to retrieve the information related to marine and atmospheric hazards, and impacts. The two-tier ML model is described in Section 4.3, followed by the main outputs resulting from its application along the Veneto coastal municipalities. At first, the results of the application of the algorithm to reanalysis data are shown to assess the performances of the algorithms, then the results obtained with future modelled input data are presented (Section 4.4). Finally, strengths and weaknesses of the proposed approach are discussed in the closing section, thus suggesting future model improvements to support the definition of disaster risk management pathways for the pilot (Section 4.5).

## 4.2. Data collection

The development of the proposed two-tier ML model requires the collection of the daily information on impacts and extreme events that occurred across the coastal municipalities of the Veneto region during the period 2009-2019 (Section 4.2.1). Additionally, estimates of future extreme events indicators, will be derived from two sets of future climate change models: atmospheric and marine projections (Sections 4.2.2.1 and 4.2.2.2, respectively).

The indicators providing insights into potential impacts were adapted from Dal Barco et al. (2024) and includes daily maximum sea surface height, the daily cumulative precipitation, the maximum value of the daily cumulative precipitation in the previous 3 days, the maximum daily precipitation in a month and maximum daily wind velocity.

on the data for historical daily indicators and extreme events (2009-2019) will form the reference dataset. Indicators derived from future climate change models will be classified between baseline dataset, for indicators relative to the historical period, and future dataset, estimated for dates after 2019. To create the baseline and future datasets, two types of scenario models will be employed:

high-resolution models incorporating all hazard indicators for mid-term analysis (until 2045), four models based on varying climate change scenarios for long-term analysis (until 2100).
Data source for each indicator is summarised in Table 5.

*Table 5. Summary of data sources for Machine Learning application in the Veneto region.*

| Indicator | Timeframe | Spatial domain | Spatial resolution | Temporal resolution | Source |
|---|---|---|---|---|---|
| *Precipitation indicators [mm]* | 2009-2019 | Europe | 5.5 km x 5.5 km | daily | CERRA[15] |
| | 2009-2045 | North-East Italy | 6km x 6km | daily | AdriaClim-WRF[16] |
| | 2009-2100 | North-East Italy | 5km x 5 km | daily | EURO-CORDEX[17] |
| *Maximum wind velocity [m/s]* | 2009-2019 | Europe | 5.5 km x 5.5 km | 3-hours | CERRA[15] |
| | 2009-2045 | North-East Italy | 5km x 5 km | daily | AdriaClim-WRF[16] |
| | 2009-2100 | - | - | - | - |
| *Maximum sea surface height [m]* | 2009-2019 | Mediterranean Sea | 1/24° (~4km) | hourly, daily | CMEMS[18] |
| | 2009-2045 | Mediterranean Sea | 1/24° (~4km) | 6-hours | CMEMS[18]+NASA[19] |
| | 2009-2100 | Mediterranean Sea | 1/24° (~4km) | 6-hours | CMEMS[18]+NASA[19] |
| *Impacts* | 2009-2019 | Veneto region | Municipality | daily | Veneto Region[20] |

### *4.2.1. Historical data collection of hazards and impacts for the creation of the reference dataset*

The reference dataset compiles information on atmospheric and marine hazards, as well as recorded impacts, with daily temporal resolution and municipality-level spatial resolution.
Atmospheric input data were collected from the Copernicus European Regional ReAnalysis (CERRA and CERRA Land; Schimanke et al., 2021; Verrelle et al., 2022). Compared to global reanalysis products, the CERRA dataset offers a higher horizontal resolution, enabling a more local-scale applications and a more accurate representation of topography and physiographic features (Verrelle et al., 2022).
Marine hazard data were obtained from the Copernicus Marine Service (CMEMS), part of the European Union's Earth Observation Programme. In particular, hourly sea surface height data were retrieved from the Mediterranean Sea Physics Reanalysis database (MEDSEA_MULTIYEAR_PHY_006_004)[15], and validated using local data from the Acqua Alta

[15] Copernicus European Regional ReAnalysis (CERRA): Schimanke et al., 2021; Verrelle et al., 2022.
[16] Model developed in the frame of the Interreg Italy-Croatia AdriaClim (Climate change information, monitoring and management tools for adaptation strategies in Adriatic coastal areas) project: https://programming14-20.italy-croatia.eu/web/adriaclim.
[17] Models provided by EURO-CORDEX (Coordinated Downscaling Experiment - European Domain): https://euro-cordex.net/.
[18] Mediterranean Sea Physics Reanalysis provided by Copernicus Marine Service (CMEMS), and developed at the Euro-Mediterranean Center on Climate Change (CMCC): https://doi.org/10.25423/CMCC/MEDSEA_MULTIYEAR_PHY_006_004_E3R1.
[19] Sea-level rise rate estimated by National Aeronautics and Space Administration (NASA): Fox-Kemper et al., 2021; Garner et al., 2021, 2023.
[20] Veneto Region – Post-Emergency Disaster Events Management Office: https://bur.regione.veneto.it/BurvServices/Pubblica/sommarioDecretiPGR.aspx?expand=19.

platform. The maximum sea surface height indicator was calculated with respect to the tide-level zero of Punta della Salute, Venice.

Finally, the impact dataset was created by collecting qualitative information from the 'State of crisis' (Stato di crisi) reports, which document damages and services interruptions caused by extreme events in the coastal municipalities of the Veneto region. This dataset comprises pairs of (day, municipality) where at least one impact was reported, excluding economic damage data due to its unavailability in public records. However, the dataset presented several limitations. Reports covered the entire Veneto region and listed affected municipalities and event dates without always specifying the exact day each municipality was impacted. Extreme events often caused inland impacts days before reaching the coast, leading to inaccuracies in the recorded impact days. To improve accuracy, each recorded impact day was manually cross-checked with local newspaper reports to resolve discrepancies.

The final dataset includes 447 days of recorded impacts caused by extreme weather events between 2009 and 2019, covering the eleven coastal municipalities of the Veneto region. Despite these efforts, detailed typologies of damages could not be associated with specific municipalities and were thus excluded from the analysis.

### *4.2.2. Modelled climate indicators for the creation of the baseline and future datasets*

Estimating future impacts require projections of climatic hazard indicators, provided by marine and atmospheric models. Projections for the historical period will form the baseline dataset, which will be used to validate the methodology and assess the quality of the results. Finally, projections for future periods will be employed to estimate future impacts.

Ideally, a single model capable of simulating both marine and atmospheric components and accounting for their cascading interactions would be used. However, no suitable unified model was available for this case study focusing on coastal municipalities of the Veneto region. As a result, separate datasets were selected for atmospheric and marine indicators.

The baseline and future datasets for marine indicators were created using sea-level trends calculated by NASA and distributions derived from reference data.

For atmospheric indicators, different models were selected based on their suitability for mid- and long-term analyses. The AdriaClim-WRF model, developed under the Interreg Italy-Croatia AdriaClim project (Fedele et al., 2024), was used for the mid-term risk analysis (up to 2045), whereas EURO-CORDEX simulations were used for the long-term estimation of impacts (up to 2100). The choice of models reflects their distinct advantages. AdriaClim-WRF model provides detailed information on daily precipitation rates and maximum wind velocity, which is crucial for understanding hazard interactions that lead to impacts. On the other hand, EURO-CORDEX models,

while lacking wind velocity data, cover a longer timeframe and offer projections for three different climate scenarios.

The estimation of indicator projections considered various climate change scenarios, such as Shared Socioeconomic Pathway (SSP) and Representative Concentration Pathways (RCP) scenarios. According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), RCP scenarios are denoted as 'RCPy', where 'y' represents the approximate radiative forcing level (in watts per square metre, Wm–2) by the year 2100", and SSP scenarios are referred as 'SSPx-y', where 'x' specifies to socio-economic trends, and 'y' indicates the radiative forcing level in 2100 (IPCC, 2023; Vuuren et al., 2011).

Table 6 outlines the scenarios used for the mid- and long-term projections, while the methodologies behind the atmospheric and marine models is detailed in the following Sections 4.2.2.1 and 4.2.2.2, respectively. For consistency, the application uses 'RCPy' notations to identify the scenarios.

*Table 6. Summary of the Shared Socioeconomic Pathway (SSP) and Representative Concentration Pathways (RCP) scenarios selected for the estimation of indicator projections in the mid- and long-term periods.*

| | ***Total daily precipitation*** | ***Maximum wind speed*** | ***Maximum sea surface height*** |
|---|---|---|---|
| *Mid-term* | RCP8.5 | RCP8.5 | SSP5-8.5 |
| *Long-term* | RCP2.6 | - | SSP1-2.6 |
| | RCP4.5 | - | SSP2-4.5 |
| | RCP8.5 | - | SSP5-8.5 |

#### *4.2.2.1. Atmospheric models*

AdriaClim-WRF model

The AdriaClim-WRF model was developed under the AdriaClim project to estimate mid-term coastal risks (up to 2045) under the RCP8.5 climate change scenario. This model utilises climate downscaling from regional (MED-CORDEX) to subregional (AdriaClim-WRF) scales, driven by one of the coupled air-sea models over the Mediterranean region provided by the Med-CORDEX coordinated initiative (Ruti et al., 2016), specifically the LMDZNEMOMED model (L'Hévéder et al., 2013). AdriaClim-WRF model provides a comprehensive set of atmospheric variables, including temperature, wind, precipitation, humidity, covering the 1990-2045 timeframe (Fedele et al., 2024).

EURO-CORDEX models

For the long-term risk analysis (up to 2100), atmospheric indicator projections were selected from available EURO-CORDEX simulations. These projections align with the IPCC's RCP scenarios, reflecting different greenhouse gas emission trajectories and socio-economic trends (IPCC, 2023). Climate change studies integrate these scenarios to represent multi-sectorial indicators (e.g.,

emissions of greenhouse gases and air pollutants, energy and land use, socio-economic and technological changes, among others; Vuuren et al., 2011). In this study, RCP2.6 (low emissions), RCP4.5 (medium emissions) and RCP8.5 (high emissions) scenarios were chosen, to represent a broad range of emission pathways.

The simulations, with an original spatial resolution of 0.10° (approximately 11 km), provide daily data on precipitation, mean and maximum temperatures, and atmospheric pressure for the 1970-2100 period. Only precipitation was selected for the analysis of future scenario analyses. Each EURO-CORDEX simulation comprises a regional climate model (RCM) with a global climate model (GCM) and includes different emission pathways (Giorgi, 2019), as listed in Table 7.

*Table 7. List of EURO-CORDEX simulations selected for the long-term risk analysis. 'Acronym' column includes the names of the simulations as referred hereinafter.*

| Acronym | Global model | Regional climate model |
|---|---|---|
| *RCA4* | EC-EARTH (Irish Center for High-End Computing, Ireland) | RCA4 (Swedish Meteorological and Hydrological Institute, Sweden) |
| *RACMO22E* | | RACMO22E (KNMI, Netherlands) |
| *CCLM* | | CCLM4-8-17 (CLM com, EU) |
| *REMO* | MPI-ESM-LR (Max Planck Institute for Meteorology, Germany) | REMO2009 (Max Planck Institute in System and Control Theory, Italy) |

#### *4.2.2.2. Marine model*

Projections of the maximum sea surface height indicator for both mid- and long-term applications were derived by combining sea-level trends provided by NASA with distributions from reference data.

This method assumes no significant impact of climate change on the variability of sea-level values around the average, consistent with current practices (Buchanan et al., 2016, 2017; Raicich, 2018; Rasmussen et al., 2018; Tebaldi et al., 2012, 2021; Wahl et al., 2017).

The procedure to create maximum sea surface height projections for each municipality includes the following steps:

- Calculate the average trend of reference maximum sea surface height values.
- Determine the residuals as the difference between each day's maximum sea surface height value and trend value.
- Estimate future sea-level trends for each scenario using NASA's sea-level increase rate (Fox-Kemper et al., 2021; Garner et al., 2021, 2023).
- Consider three scenarios based on SSP and RCP combinations: SSP1-2.6, SSP2-4.5, and SSP5-8.5.

- Randomly extract a residual value for each day in the future period, ensuring alignment with the corresponding municipality, calendar month and lunar phase from the reference dataset.
- Combine scenario-specific sea-level trends with selected residual to generate the baseline dataset (2009-2019) and future datasets (2020-2100) for each municipality and scenario.

## 4.3. Methodology

### *4.3.1. Machine Learning model development*

Machine Learning (ML) algorithms offer a new path to address the analysis of multiple environmental hazards and to model future climate change impacts due to their ability to model complex feedback and non-linear interactions between different variables, without the need for an explicit modelling.
In Dal Barco et al. (2024), the authors analysed the risk of impacts along the coastal municipalities of the Veneto region within the 2009-2020 timeframe and developed a ML tool able to estimate, for each day and municipality, a risk score representing the likelihood of an impact. However, the analysis does not include any estimation of future impact trends. This application starts from the methodology described in Dal Barco et al. (2024) and aims to develop a two-tier ML methodology capable of estimating the number of days per year in which at least an impact occurs along the Veneto coastal area given the knowledge of daily local atmospheric and marine indicators or indicator projections. This tool will provide an insight of the effects of climate change on impact trends.
The input data of the analysis is composed of a set of environmental features for each day in the timeframe 2009-2019 and for each municipality on the Veneto coastal area, and by a boolean variable representing the presence of an impact on the same day and location that will be used as output label. As the purpose of this application is the estimate of the number of days per year with impacts, the dataset should be structured with yearly samples. In this way, the input dataset would be composed of 10 samples (one per year), and with more than 20000 features (i.e., 11 municipalities × number of indicators × 365 days), and could not be used to train any supervised ML tool, as the number of input features would be much bigger than the number samples. To overcome this problem, several different approaches have been considered, including time series, use of statistics of indicators, convolutional neural networks. Eventually, a novel two-tier approach was developed (Figure 12). In the first tier the number of features in each yearly sample is strongly reduced by estimating with a first ML tool a risk score value for each couple (day, municipality); this step is a binary classification performed using a supervised ML algorithm and it is described in detail in Dal Barco et al. (2024). The results of the first tiers are then manipulated to create the input of the second tier: the daily risk score data are grouped in yearly samples using a moving window and binned in risk classes. Then, in the second

tier, the number of days per year in each class are the input of the linear regression tool which calculates the total number of days featured by the occurrence of impacts associated to extreme weather events per year.

This method leveraged well-known ML algorithms to exploit the real-time relationship between indicators and impacts effectively. The novelty of the proposed approach does not rely on the implemented ML methods, but on the way these aggregating methods are combined, which allowed the integration of daily input features and impacts to calculate the cumulative yearly values of impacts despite the skewness of the input dataset.

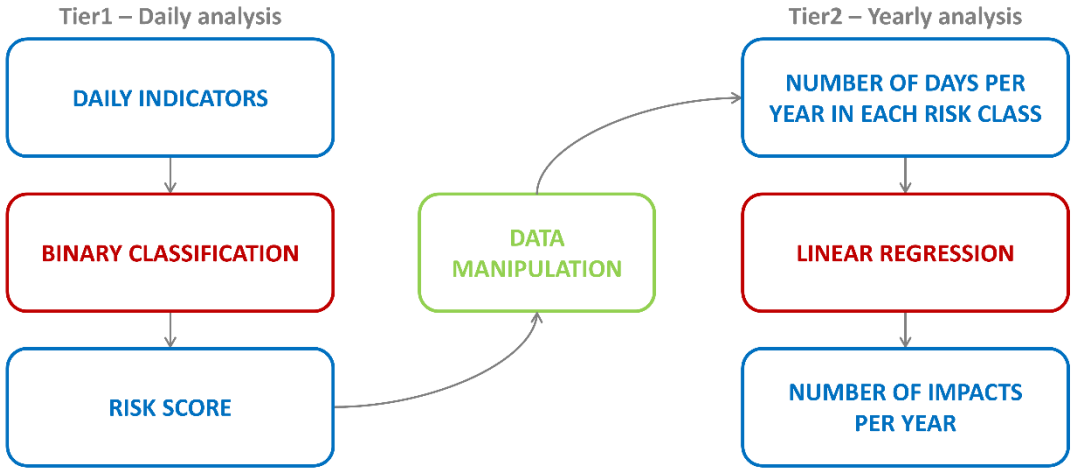



*Figure 12. Scheme of the two-tier approach.*

*4.3.1.1. Tier1: ML algorithm to evaluate the daily risk score*

The first tier aims at estimating the risk score for each day and municipality, which is a measure of the probability of an impact occurring at that location on that day. Since this first step follows the previous application of the authors (Dal Barco, Maraschini, et al., 2024), the methodological approach is not discussed in detail.

Each sample of the input dataset is associated with a day and a municipality: the input features are the atmospheric and marine indicators (Table 5), plus the municipalities and the months of the year, and the output label is the presence/absence of impacts.

This is a binary classification problem on a skewed dataset (as the number of days with impact is about 1% of the total number of days). A Multi-Layer Perceptron algorithm has been trained with sample weights to keep the minority class in the right account, validated, and tested. The output of the application on a new input sample is the corresponding risk score, which is a measure of the probability of the occurrence of an impact on that (day, municipality).

It is worthwhile to note that the outcome of this algorithm is as reliable as its input data: when it comes to look at future climate projections, the results, as the corresponding modelled data used as

input, will not reliable on a daily basis, however their statistical distribution over several years, and hence the number of days with high values of risk score, is reliable.

Because of the skewness of the input data and the consequently use of weights in the codes, it is not possible to calculate the number of days with impacts per year as the sum of the risk scores. Similarly, it is not possible to set a threshold in the risk score, define any value with risk score above the threshold as day with impact and sum them up: in a binary classification on a skewed data if the recall is sufficiently high (i.e., most positive events are correctly identified), the precision is likely to be very low (i.e., there will be a high number of false positive). This makes the total amount of predicted positive an overestimate of the correct number of positives. These considerations led to the creation of a second algorithm, that takes as input the daily risk scores and output the number of days with impact per year.

*4.3.1.2. Tier2: ML algorithm to estimate annual extreme weather impact*

The second tier is aimed at estimating the number of days per year in which at least one impact is expected along the Veneto coastal area using as input the knowledge of the daily risk scores previously calculated. In order to achieve this goal, the dataset was structured using yearly samples. The feature of each sample is characterised by the 365 values of the risk score for the 11 municipalities, i.e., approximately 4000 features; the output label is the number of days with at least an impact on the Veneto coastal area. The total number of samples is 10: the number of full years in the timeframe. As the number of features is much smaller than the number of samples, to create a ML algorithm it is necessary to reduce the number of features and increase the number of samples. The increase of the number of samples was obtained by the implementation of moving windows sampling: instead of considering 10 non-overlapping years, a year was defined as any interval of 12 consecutive months. Since samples adjacent in time are not independent from each other, making a random splitting a non-viable option, the data was split chronologically between train and test before the moving window process. To reduce the number of features, the risk scores of each sample were binned with a user-defined number of classes (i.e., risk classes), and the number of samples falling in each bin was calculated. The number of events per year falling in each class are the features of the yearly samples. Finally, a linear regression algorithm with non-negative coefficients and zero-intercept was implemented estimating the number of annual impacts derived from the number of days in each risk class. The algorithm is then trained, validated and tested, and the results are reported in Section 4.4.2.1.

### *4.3.2. ML application to future scenario data for the estimate of future impacts*

In order to implement the developed ML methodology to the estimate of future impact, the data must meet the requirements for a correct application (Section 4.3.2.1). Then, the ML model is applied to mid-term modelled hazard data to analyse the non-linear effects between hazards (Section 4.4.2.2), and finally to multiple climate change models until year 2100 (Section 4.4.2.3).

#### *4.3.2.1. Comparison of the distributions of the reference data and the modelled data in the reference timeframe*

The consistency of the dataset for reference and baseline in the reference timeframe (2009-2019) needs to be checked. In particular, the data used to train, validate, and test the ML algorithms should have a distribution as close as possible to the distribution of the modelled data used to estimate future impacts. In other words, the algorithm can be applied to new data (i.e., the modelled data) as long as the distributions of the extreme values of the reanalysis and the modelled data are spatially and temporally comparable.

The distribution between reference and baseline values of maximum sea surface height are the same because of the methodology used to create the modelled data, which is based on a random sampling of the reference values (see Section 4.2.2.2).

More attention must be devoted to the atmospheric indicators: for the reference datasets these indicators were retrieved from the CERRA dataset, while the modelled data are retrieved by the AdriaClim-WRF model for the mid-term predictions and for the EURO-CORDEX models for the long-term predictions (see Section 4.2). Figure 13 shows the distributions of both reference and baseline datasets for three selected atmospheric indicators within the reference timeframe 2009-2019. For the wind indicator, higher values are observed in the baseline dataset compared to the reference (Figure 13a). For both rain indicators, instead, the reference data present a thicker tail distribution, highlighting a slightly higher precipitation level (Figure 13c, Figure 13d). However, the distributions of the two datasets are comparable, which allow the further application of ML algorithms to modelled data.

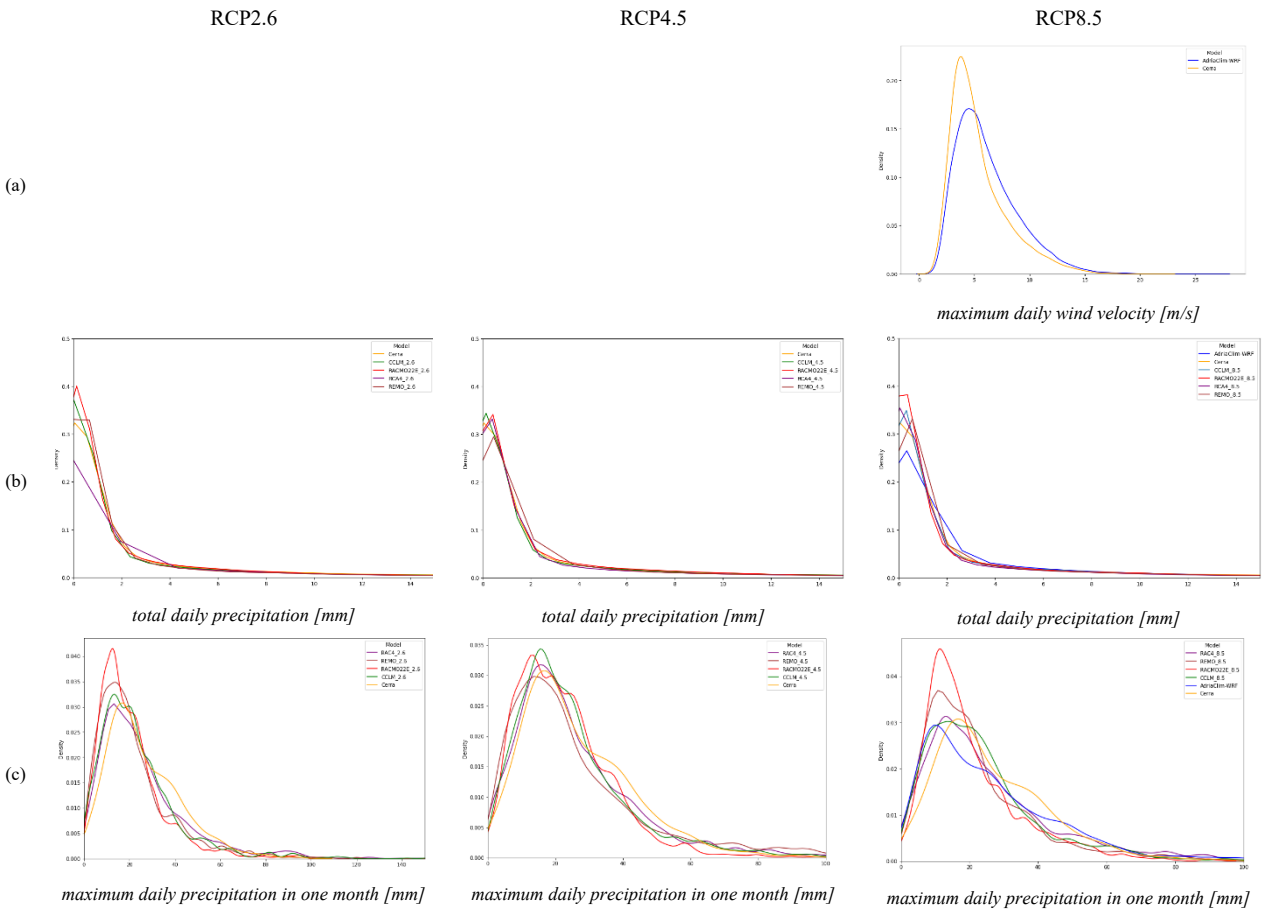



*Figure 13. Distribution of (a) maximum daily wind velocity, (b) total daily precipitation, and (c) maximum daily precipitation in a month from the CERRA reanalysis against AdriaClim-WRF and EURO-CORDEX datasets (under different climate change scenarios – i.e., RCP2.6, RCP4.5, RCP8.5) within the historical period (2009-2019).*

#### *4.3.2.1. Mid-term risk analysis with synergistic interaction of hazards using the AdriaClim-WRF model*

The main aim of this application is to understand the contribution of the different marine and atmospheric indicators (i.e., precipitation, sea-level, wind velocity) in relation to the annual probability occurrence of impacts for the upcoming decades. This analysis will provide information on the relative importance of each potential hazard and their combination (Teichert et al., 2016).

The comparison of coastal impact trends across different combinations of hazards provides a more comprehensive understanding of how climate change will exacerbate these impacts. This analysis explores the influence of individual hazards, their interactions, and the effects of the non-linearities in the system. Figure 14 shows the combination of hazards identified for this study, and Section 4.4.2.2 presents the results of future annual risk estimations.

The input of these analyses are the indicator projections for daily maximum sea surface height, the daily cumulative precipitation, the maximum value of the daily cumulative precipitation in the previous 3 days, the maximum daily precipitation in a month and maximum daily wind velocity,

which are considered the main responsible for coastal impacts along the Veneto littoral, especially within the 2009-2019 timeframe (Dal Barco, Maraschini, et al., 2024). When a hazard is accounted, the related indicator projections assume the values calculated by climatic models following the RCP8.5 climate change scenarios. Conversely, when a hazard is not considered, the indicator projections are set to the average of the indicator values in the reference period. In other words, if a hazard is excluded, the corresponding indicator assumes realistic and non-extremes conditions, ensuring that the hazard cannot contribute to any impacts predicted by the model. The outputs of these analyses are the future trends of coastal impacts until year 2045 for each hazard combination; their comparisons highlight the relative importance of the stressor and uncover non-linearity effects of compounding hazards.

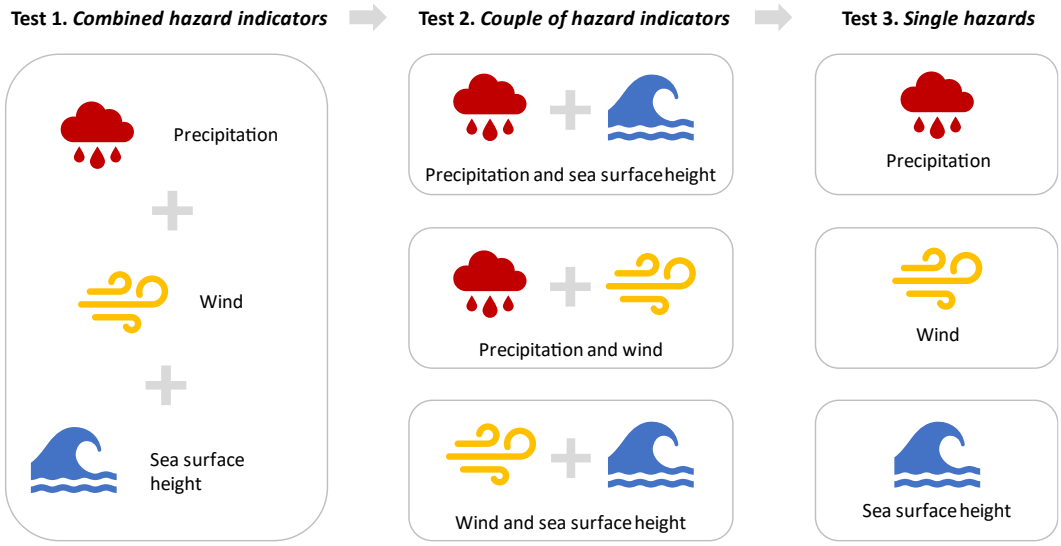



*Figure 14. Iterative combination of the selected hazards to estimate future risks.*

#### *4.3.2.2. Long-term risk analysis for multiple climate change models using the EURO-CORDEX models*

In order to estimate future impacts dependent on climate change scenarios, hazard indicators modelled for different Representative Concentration Pathway (RCP) scenarios were required to be integrated into the developed ML algorithm. In particular, the scenarios considered for this application were RCP 2.6, RCP4.5 and RCP 8.5.

For each of the RCP scenario, one maximum sea surface height dataset was created, as described in Section 4.2.2.2. As far as the atmospheric hazard indicators are concerned, the four models introduced in Section 2 were considered. In particular, for each model, datasets from the three RCP scenarios were extracted. Combining both marine and atmospheric datasets, a total of 12 input datasets were created.

Both tiers of the algorithm were then applied to the 12 datasets, and the corresponding impact trends for the Veneto coastal area were estimated.

On top of the four models, for each scenario the results for an ensemble model were calculated. In order to create the ensemble model for each scenario, the option of averaging the indicator data for each day of the timeframe was quicky discarded, as its smoothing effect would have reduced the extreme values, which are the main drivers of the impacts. Conversely, the ensemble model for each scenario was created by considering the results of Tier 1 of the developed ML model for each of the four models and calculating the number of days following in each class. Then, the number of days in each of the high-risk class was averaged between models, and the average number of days per class was used as input the second algorithm.

## 4.4. Results

As described in Section 4, the results of the application of the proposed two-tier ML-based approach to the Veneto coastal area are presented in the following sections. In particular, the model validation and testing for the estimation of the annual occurrence of impacts is presented in Section 5.1, whereas Section 5.2 is devoted to the application of the two-tier approach with modelled data over the reference period, followed by its application to different climate change scenarios estimating the occurrence of impact risks along the coastal municipalities of the Veneto region (Italy) in the mid- and long-term future (Sections 5.3 and 5.4, respectively).

### *4.4.1. ML model testing*

The training and the testing of the proposed algorithms are performed separately for the mid- and the long-term analysis, as the latter does not include the wind indicator, and the algorithm needs to be trained and tested again without it. Figure 15 depicts the training and testing of the algorithm developed for the mid-term and long-term analysis, comparing the recorded (in orange) and predicted (mid-term in purple, and long-term in blue) impact frequency over time. The results obtained by the algorithms for both analyses are quite similar. Only a slight performance loss for the results of the long-term analysis is noted, as the wind indicator information is missing. There is a good agreement between both sets (i.e., between the number of predicted and recorded impacts): the similar quality of the results between train and test excludes the risk of overfitting. The least square error (i.e., the median of the squared distance between the number of predicted and recorded impacts) on the test sets is approximately 2 impacts for both mid- and long-term analysis, which is approximately the 20% of the average number of impacts per year. The determination coefficient R2 relative to the correlation between recorder and predicted number of impacts on the test set is 0.57 for the long-term analysis and 0.60 for the mid-term analysis. This result is quite satisfactory, given the uncertainty of the input data, hence the tested algorithm is now ready to be applied to new data.

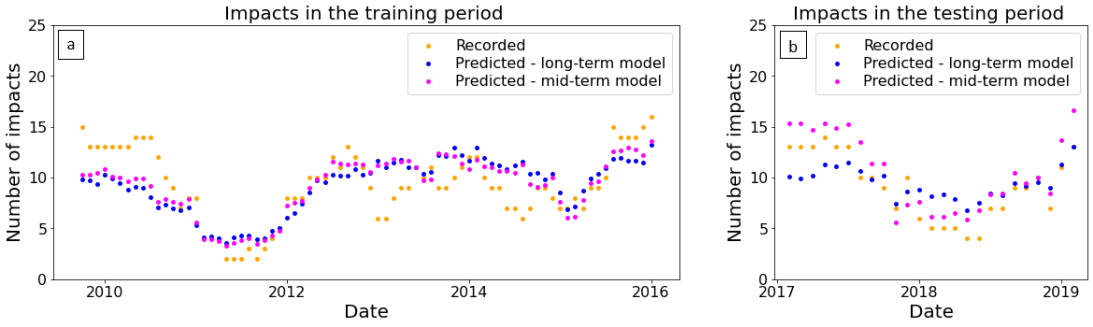



*Figure 15. Comparison of recorded number of impacts, number of impacts predicted by the mid-term algorithm, number of impacts predicted by the long- term algorithm: (a) train dataset; (b) test dataset.*

### *4.4.2. Application of the two-tier approach to estimate the annual occurrence of impacts*

Once the Machine Learning (ML) models are implemented and tested in the reference period, they can be applied to new input data. In order to estimate future occurrence of impacts in relation to climate change scenarios, modelled data were integrated, only after having checked that their distribution in the reference period is similar to the one of data used for training and testing (Section 4.4).

#### *4.4.2.1. Validation of the impact predictions*

In order to validate the results of the algorithm, the ML models are applied to the baseline datasets - i.e., datasets containing projection of the indicator values evaluated during the historical timeframe, when the recorded impacts are available.

ML models have been applied to the baseline datasets created by both AdriaClim-WRF and EURO-CORDEX baseline datasets (described in Section 4.2.2), and their results have been compared with the recorded impacts (Figure 16 and Figure 17). It can be noted that the outputs of the three different climate change scenarios (i.e., RCP2.6, RCP4.5 and RCP8.5) do not significantly differ during the historical period (Figure 17). This is expected, as the projected indicators for the three scenarios are almost identical in the historical timeframe, diverging gradually with time in the future timeframe. The results of these analysis are affected by two distinct sources of errors: the errors introduced by the ML algorithms (discussed in Section 5), and the error induced by modelling of input data. The error due to the ML algorithm (i.e., distance between blue and orange dots) is much smaller than the total error (i.e., distance between green and orange dots), meaning that the main approximation introduced by the application of the tool is related to the modelling of the input data, rather than to the algorithm. More specifically, both figures show how the results obtained by modelled data are not able to predict the yearly variability of the collected data, and in general underestimate or misplace the number of days with impacts. The analysis of the indicators' distribution (Figure 13) highlights

that modelled indicators present lower precipitation levels compared to reanalysis. This is likely to be the cause of the underestimation of impact. However, the order of magnitude of the yearly impact is comparable. These results suggest that the application of the algorithm to future modelled data allows a reliable estimation of the trends of the impacts, with a possible underestimation or misplacement of the peaks caused by precipitation extremes.

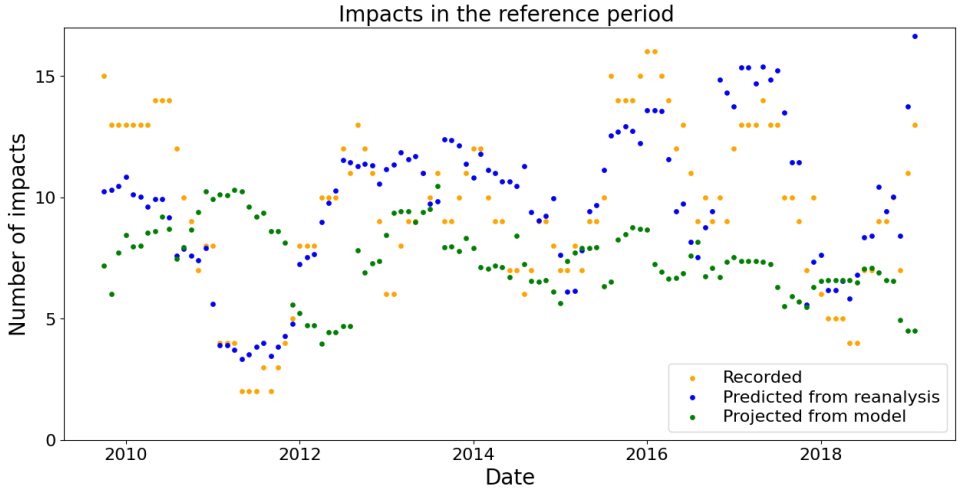



*Figure 16. Comparison of recorded impacts, impacts predicted from the reanalysis data and impacts predicted from the AdriaClim-WRF model.*

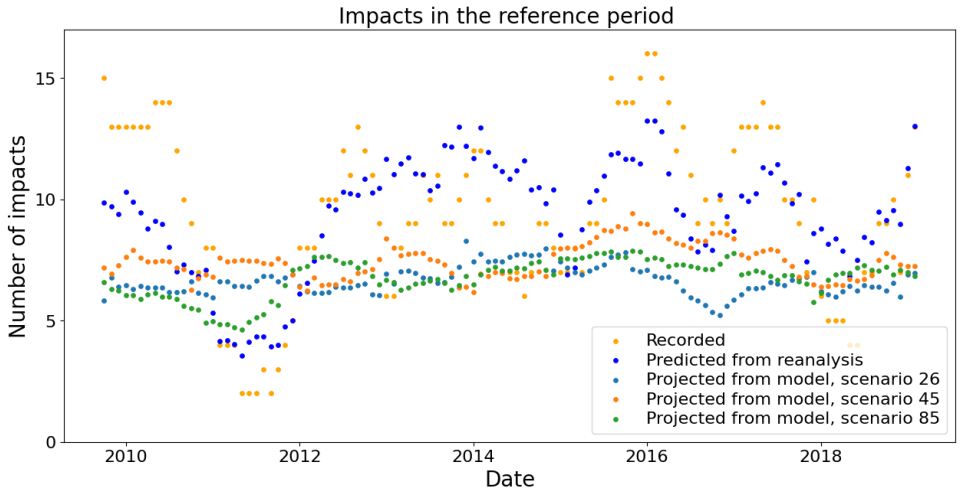



*Figure 17. Comparison of recorded impacts, impacts predicted from the reanalysis data and impacts predicted from the EURO-CORDEX simulations for the three considered scenarios.*

#### *4.4.2.2. Mid-term risk analysis with synergistic interaction of hazards*

Once the algorithm for mid-term prediction was tested on the reference period, it has been applied to the AdriaClim-WRF model for the 2020-2045 timeframe to estimate future risks. To better understand the contribution of the different hazards in the calculation of the annual occurrence, multiple sensitivity analyses were run, as described in Section 4.3.2.1, to better understand the

contribution of different combinations of the selected hazards (i.e., total daily precipitation, maximum sea surface height, wind velocity). Because of the non-linearity of multi-risk phenomena (there may be days in which each hazard is not enough to create an impact, but their combination is), and because there may be days when multiple hazards created an impact independently, the estimated risk caused by combined hazards is not the sum of the impacts of the single hazards. Figure 18 highlights the different combinations of hazards.

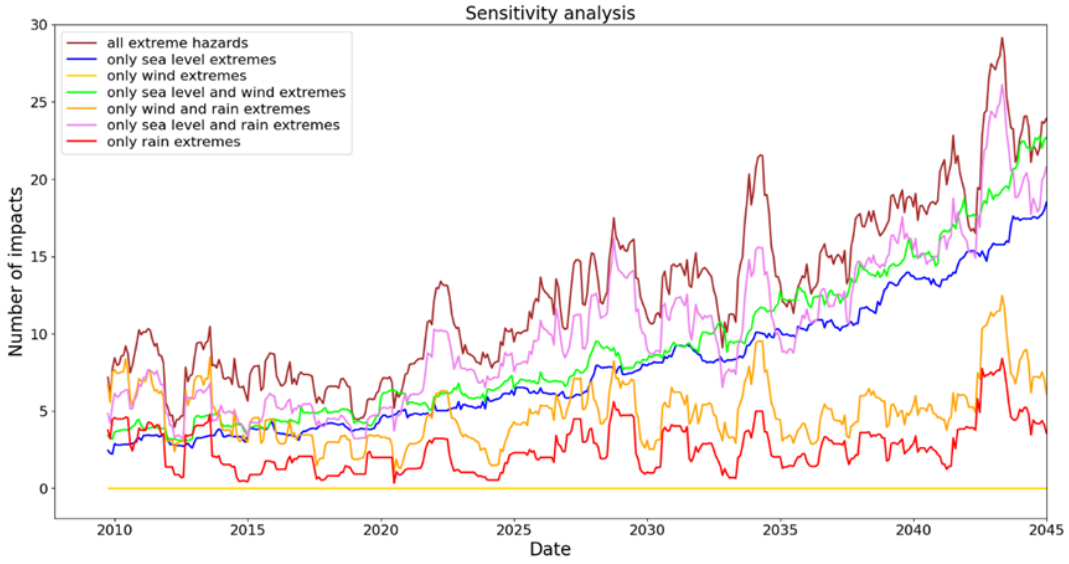



*Figure 18. Sensitivity analysis: comparison of projected risks for different types of hazards.*

When all the extreme hazards are considered (depicted in *brown*), there is an overall increase in future risks, with sustained variability. The analysis of the contribution of individual hazards has been performed to understand the different contributions.

The increasing trend of risks is mainly due to the trend of sea-level extremes (*blue*), and this can be explained by the fact that sea-level rise contributes to a slow but continuous increase of hazard-related phenomena, including coastal erosion and storm surge frequency (Mentaschi et al., 2018; Nicholls et al., 2007). The high variability embodied by the peaks and troughs are associated with the impacts caused by extreme precipitation events (red) and is reflected in the combination with the other hazards (*orange*, *pink* and *brown*).

Wind extremes (*yellow*) seem not to produce impacts alone. However, the presence of the wind extremes coupled with the sea-level extremes (*green*) or with precipitation extremes (*orange*) will increase risks compared to the risk generated by sea-level (*blue*) and precipitation extremes alone (*red*) (Marcos et al., 2019).

This behaviour can be explained by the typical characteristics of thunderstorms (combination of intense precipitation and strong winds; Jelic et al., 2021) and storm surges (combination of high sea surface height and strong winds).

According to this analysis, which does not consider adaptation measures, impacts will increase over time due to climate change along the Veneto coastal zone. This increase will mainly be caused by the increase in extreme sea-level events; however, there is no evidence (but it cannot be excluded) that the number of impacts may further increase because of rain or wind extremes.

#### *4.4.2.3. Long-term risk analysis for multiple climate change models*

The long-term estimation of coastal risks along the Veneto coastal municipalities performed for the four EURO-CORDEX models and the corresponding ensemble model is shown in Figure 19. As described in Section 4.3.2.2, the models collect the information related to sea surface height and precipitation until year 2100 for three different Representative Concentration Pathway (i.e., RCP2.6, RCP4.5, and RCP8.5). Unfortunately, the maximum wind velocity indicator was not included in the long-term application, as its bias corrected version is not yet available.

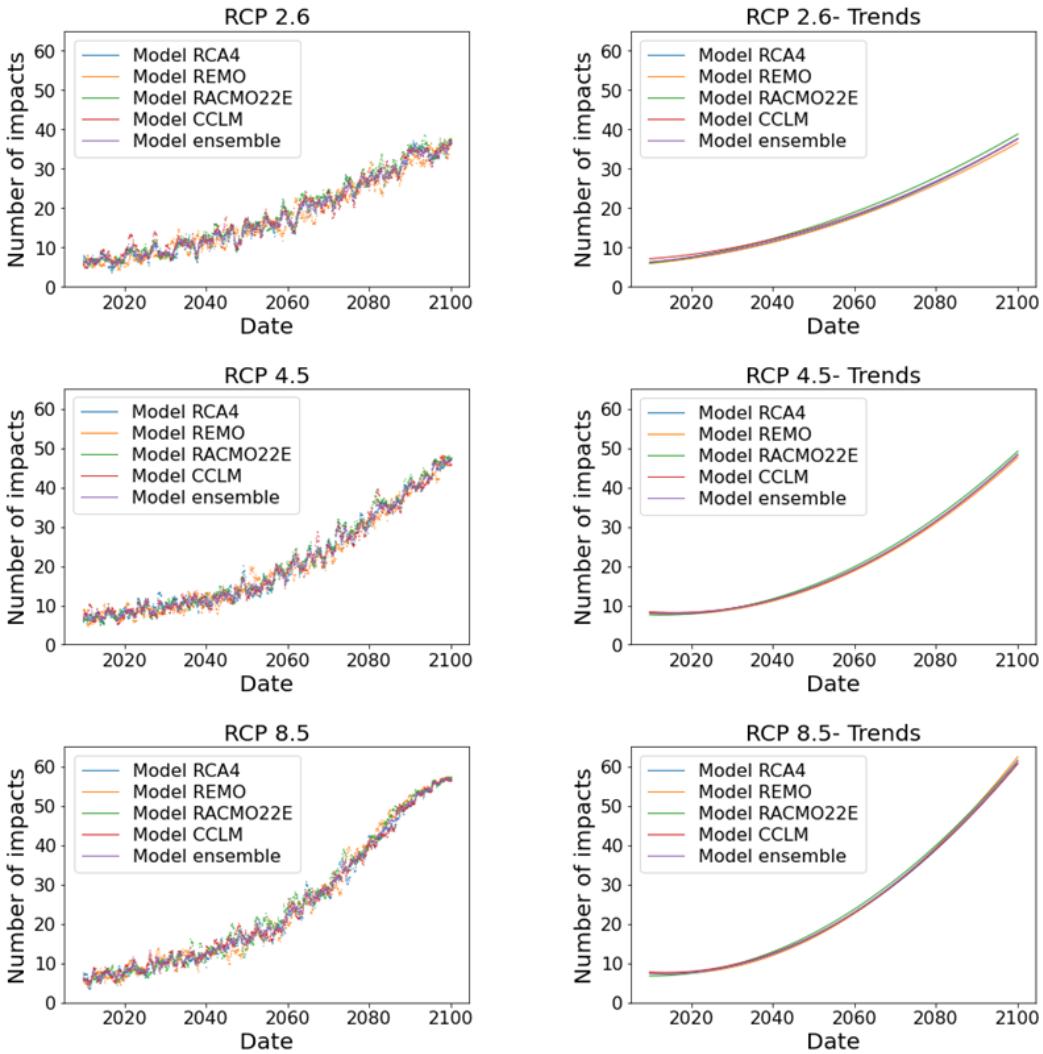



*Figure 19. Coastal risk estimations and trends until year 2100, according to three different Representative Concentration Pathway (i.e., RCP2.6, RCP4.5, and RCP8.5) for the four different models (i.e., RCA4, REMO, RACMO22E, CCLM) and the ensemble model.*

For each RCP scenario, the estimated number of impacts across the analysed models (i.e., RCA4, REMO, RACMO22E, CCLM) and the ensemble model shows a strong. The models project very similar impact trend, with only minor variations in timing of peaks and throughs, mainly influenced by differences in the seasonal fluctuation projected by each model. Given the high consistency among the models and to ensure no information is overlooked, the following discussion focuses exclusively on the ensemble model, which integrates data from all individual models (Figure 20).

In accordance with the mid-term estimations (Section 4.4.2.2), the occurrence of coastal impacts estimated by the EURO-CORDEX ensemble model is expected to increase until the end of the century, with notable differences between RCP scenarios. As expected, the lower number of impacts at the end of the century is estimated by the lower emission scenario (RCP2.6), with about 35 impacts per year, followed by the mid-emission scenario (RCP4.5) with about 50 impacts per year, and by the higher emission scenario (RCP8.5) reaching a value of 60 impacts at the end of the century. It can be noted that the results relative to the highest emission scenario are in line with the results of the mid-term assessment, performed in Section 4.4.2.2.

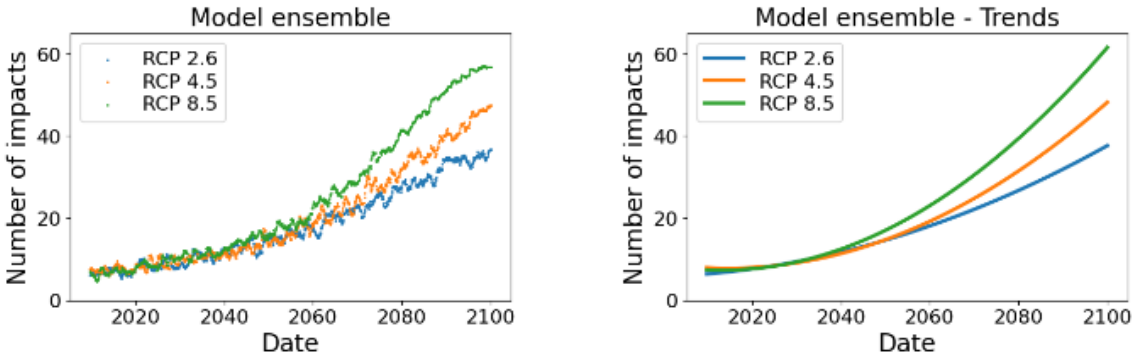



*Figure 20. Coastal risk estimations and trends until year 2100, given by the ensemble model against three Representative Concentration Pathway scenarios (i.e., RCP2.6, RCP4.5 and RCP8.5).*

The difference trend between the three scenarios becomes clearer later in the century. Starting from the year 2040 onward, impacts calculated according to RCP8.5 present a steepest growth curve. Then, the other two scenarios (i.e., RCP2.6 and RCP4.5) split their paths around the year 2060.

Finally, the estimates depicted on the left of Figure 20 show a change of the curvature of the impact curve for RCP8.5, suggesting a slowing-down in the growth of impacts towards the end of the century. However, it is not possible to ascertain the causes of this growth slowdown.

The main result of the analysis is that the expected number of impacts at the end of the century along the Veneto coastal area ranges between 35 in the low emissions scenario and 60 in the high emissions scenario, which are respectively approximately 5 to 10 times more than today. This result suggests that the development and implementation of tailored adaptation strategies for the investigated study area should be a priority.

## 4.5. Discussion

This study proposes an innovative methodology to calculate risk as the number of days when at least one impact caused by extreme weather events occurs in the coastal municipalities of the Veneto region. This approach is then applied to future climate change scenarios, providing critical insights into evolving risks. To the best of the authors' knowledge, this is among the first studies to explore, develop and implement Machine Learning models specifically designed to estimate risks under future climate change scenarios, marking a significant advancement in multi-hazard risk assessment (Allegri et al., 2024; Zennaro et al., 2021).

The paper's objectives present various challenges related to the different steps of the analysis. The estimation of impact frequency is not derived from time series or on statistical analysis of the indicators but relies on daily local indicators. This approach has the advantage of leveraging specific information that associates certain daily indicators values to the occurrence of impacts, which would be lost in time series approaches. To the authors knowledge, this represents the first attempt to estimate the cumulative number of positives (i.e., the total number of impacts in one year) in a binary classification problem involving a skewed dataset within the environmental field. Specifically, it determines the probability of an impact for each day and municipality. The task was particularly challenging due to the nature of binary classification on skewed datasets: achieving reasonably high recall (i.e., correctly identifying positive events) often results in relatively low precision (i.e., a high number of false positives). Consequently, the total number of predicted positive events tends to overestimate the actual number of impacts. To address this challenge, a novel two-tier methodology was implemented, combining simple and well-established ML tools in an original configuration. The results were satisfactory, with an error margin of approximately 20% in estimating the number of impacts in the test set.

The major limitation in implementing the algorithm was the quality of the input dataset, and particularly the impact dataset. The reliance on 'Stato di Crisi' reports introduces significant gaps, as these reports typically only list affected municipalities and dates without reporting precise event details. Furthermore, impacts that did not trigger a 'Stato di crisi' are absent, even when they caused major damages or disruptions. These challenges were partially overcome by manual verification of events. However, the magnitude of each impact or the total number of impacts per each municipality is not measured. This lack of detail hinders the ability to estimate the total number of impacts across the area, or assess the associated economic losses. Additionally, the absence of specific impact location data prevents consideration of local vulnerability and exposure factors in the analysis. If more detailed information on impact locations and economic losses were available, geographic, hydrographic and geological data, along with infrastructure maps, could be integrated into the

analysis. Similarly, socio-economic dynamics (e.g., urbanisation, population growth, migrations, tourism, economic activities) could be included to evaluate how these factors interact with climatic drivers to exacerbate risks and vulnerabilities. For instance, the low frequency of recorded impacts in the southernmost part of the region, corresponding to the river Po delta, reflects the human-based nature of the dataset, which prioritise impacts on urban settlements while neglecting natural ecosystems and protected areas. Moreover, if details about the characteristics of impacts were available, the plethora of assessment endpoints could have been expanded to include different types of damages (e.g., structural damage, flood damage, water quality alteration, infrastructure disruption). These considerations underscore the need for a standardised impact dataset, created through collaborative efforts between local authorities and the scientific community. Such a dataset would significantly improve the quality of multi-risk studies and facilitate knowledge-sharing among researchers. Further advancements to the algorithm could be achieved by leveraging additional data sources, such as satellite imagery or unstructured text mining, to extract more comprehensive information about impacts.

The development of the algorithm adhered to the robustness and explainability guidelines for artificial intelligence outlined by JRC (Hamon et al., 2020). Its robustness was validated through testing on new dataset to minimize overfitting. Reproducibility is ensured through implementation in a dedicated environment with hardcoded random seeds, while transparency is maintained through the use of Python libraries. A sensitivity analysis further enhances the explainability of the algorithm.

No sensitive data were used in training or testing the algorithm. Importantly, the algorithm is not intended for autonomous decision-making that could directly impact people's lives. Instead, it is designed as a decision-support tool to help researchers and local authorities to enhance understanding of the factors driving impacts along the Veneto coast.

To maintain relevance and accuracy, it is recommended to regularly retrain or fine-tune the algorithm with new and updated data, considering evolving dynamics or incorporating new future projection models.

The second objective of this study was to apply the developed algorithms to estimate the future occurrence of impacts. The main challenge of this task is that ML algorithms are generally designed for datasets with the same distribution as those used for validation and testing. This requirement is not automatically satisfied when algorithms are applied to modelled data, such as future scenario dataset. To address this, a data analysis, including a distribution comparison of extreme values of indicators, was performed before applying the algorithm. Additional tests were carried out comparing the estimated number of events derived from modelled data with those from reanalysis data over the reference period 2010-2019. The distribution comparison was conducted for atmospheric indicators

only, as the marine model was specifically designed to preserve the distribution of extremes. For atmospheric indicators, a general agreement was observed between the reanalysis and the modelled data distributions in the reference period, particularly in the extreme hazard value range. However, the reanalysis data showed a thicker tail in the rain indicator distribution, indicating that the model slightly underestimated the number of days with heavy rain. This aligns with the comparison of forecasted impacts versus recorded impacts during the reference period: while the magnitude and trend were accurate, annual peaks were often underestimated. This suggests that the algorithm struggles to predict years with unusually high occurrences of extreme rain events when applied to modelled data. As a result, the tools are reliable for identifying trends but may underestimate year-to-year variations.

An error analysis was conducted by comparing recorded impacts, impacts estimated from reanalysis data, and impacts estimated from modelled data during the testing period. The analysis revealed that the error introduced by the algorithm (i.e., the distance between recorded data and reanalysis estimates) was significantly smaller than the error introduced by the modelled data (i.e., the distance between estimates from models and reanalysis). This emphasises the importance of selecting models, whose distributions closely match those of reanalysis data, particularly in the range of extreme values. The results could be improved if marine and atmospheric data were generated by the same model. Unfortunately, such a model was unavailable, as most marine models tends to underestimate extreme values of sea-level.

The methodology was then applied to two sets of future projections to infer the number of impacts in mid- and long-term future scenarios. The mid-term risk analysis focused on the contributions and interactions of hazard indicators up to 2045 under RCP8.5. A key finding was the significance of non-linear effects between different hazards: the combined impact of multiple hazards was greater than the sum of their individual impacts. The analysis also projected a general increase in the number of impacts, comprising a rising trend and high-frequency oscillations. The increasing trend is driven by the growth in sea-level extremes over time, attributable to sea-level rise (Mentaschi et al., 2018; Nicholls et al., 2007). In contrast, the year-to-year variability is likely linked to extreme precipitation events. Given the potential underestimation of extreme rain events, it is reasonable to assume the trend of increasing impacts is reliable, while oscillations around the trend may be underestimated.

The long-term risk analysis utilised four models under three future scenarios (RCP2.6, RCP4.5, and RCP8.5) to project impacts until 2100. A limitation of this analysis was the lack of maximum wind velocity projections, which were unavailable at the time of the application. Despite this, the long-term projections allowed for a robust comparison of future impact trends across different emission pathways. The expected increase in the number of impacts along the Veneto coastal area are worrying.

By the end of the century, the number of impacts is expected to be at least five times higher under the low emissions scenario (RCP2.6) and ten times higher under the high emissions scenario (RCP8.5). The results under the low emissions scenario reflects the inertia of the system: even with immediate emission reduction, the consequences of past emissions will persist for decades (IPCC, 2023). These projections underscore the urgent need for tailored adaptation strategies for the region. Notably, differences in results across different atmospheric models were minimal, as sea-level rise was primary driver of impact in the analysis.

Despite its limitations, this study has significant implications for coastal management and planning. The findings contribute to the ongoing development of the Regional Strategy for Climate Change Adaptation (SRACC; Regione del Veneto, 2024), which integrates these insights to refine management plans. A combination of grey, green, and hybrid solutions has been implemented to protect coastal communities and the environment. Grey infrastructures, such as groins, barriers, and breakwaters, safeguard urban developments and cultural heritage sites like Venice and its lagoon, with support from the MOSE system. Meanwhile, nature-based solutions, such as dune restoration and preservation, strengthen ecosystem resilience against seasonal extreme storm surges.

## 4.6. Conclusion

This paper aims to develop a novel methodology for estimating climate-related impacts on the Veneto coastal area using daily hazard indicators, and applying it to future climate models to assess the correlation between impacts and climate change.

Estimating impact frequency from daily hazard values presents significant challenges. To address this, an original two-tier methodology is proposed. The first tier determines a daily risk score for each municipality, quantifying the likelihood of an impact to occur at the specific location and day. The second tier utilises these daily risk scores to estimate the annual number of days with at least one impact expected along the Veneto coastal area. Despite limitations, primarily related to impact data, the algorithm's application to test data yields satisfactory results. The proposed model is highly flexible and can be easily applied to different locations, sets of indicators, and even scientific fields, as long as the objective involves the estimation of cumulative positives in a binary classification problem with a skewed dataset.

The algorithms were then tested on modelled data and subsequently applied to future scenarios. The key findings from the mid-term application emphasise the necessity of multi-hazard analysis to account for nonlinear interactions between hazards. The observed increase in the impact trend is deemed reliable and primarily driven by sea-level rise, while year-to-year variations are attributed mostly to precipitations and are likely slightly underestimated. In the long-term application, the study

projects a dramatic increase in the number of impacts under both best- and worst-case scenarios, underscoring the urgent need for mitigation and adaptation strategies.

Future developments for the model include improving the input database, particularly the impacts data, through advanced technologies like remote sensing and unstructured text mining. Additionally, integrating coastal adaptation strategies within the algorithm would enable sensitivity analyses of their effectiveness. Finally, exploring the potential of more advanced and sophisticated algorithms, such as Recurrent Neural Networks or Graph Neural Networks, could enhance the estimation of risk scores by capturing temporal and spatial relationships between samples.

# Chapter 5. *Third paper*[21]

# Prioritise risks and improve adaptation strategies in the Veneto coastal area through the application of a custom AI tool

**Abstract.** Climate change has emerged as one of the most severe global challenges of our time, with rising temperatures and unprecedented shifts in climate patterns. Coastal areas are particularly vulnerable, facing compounded impacts from sea-level rise and increasingly frequent extreme weather events. These growing threats demand urgent need for proactive and comprehensive adaptation measures to protect coastal regions, which have been recently defined sentinels of climate change.

A paradigm shift towards a multi-hazard and multi-risk perspective is increasingly recognised as essential in risk assessment and management. Moreover, Artificial Intelligence (AI) have emerged as promising tools to aid decision-making processes in coastal risk management and climate change adaptation. This study introduces COAST-AId, a custom Large Language Model designed to facilitate the analysis and synthesis of diverse information relevant for climate risk assessment and management in the Veneto coastal area. The tool facilitates the application of the risk assessment framework proposed in the European Climate Risk Assessment (EUCRA) and tailor it to analyse the specific climate risk challenges of this region. The framework combines three key dimensions – i.e., risk identification, risk analysis, and policy analysis – to prioritise risks and define urgent actions. The application of the COAST-AId tool was performed in close cooperation with local stakeholders involved in the MYRIAD-EU project where a systemic multi-hazard risk framework is considered to support the development of disaster risk management and climate adaptation pathways.

The performance of the tool was evaluated by stakeholders, highlighting critical risks in the Veneto coastal area as well as gaps and opportunities for enhancing coastal resilience and improving risk reduction and adaptation strategies at the regional to local scale.

[21] This Chapter is derived from Dal Barco et al., "Prioritise risks and improve adaptation strategies in the Veneto coastal area through the application of a custom AI tool", submitted to *Communications Earth & Environment*.

## 5.1. Introduction

Climate change impacts have become increasingly severe along coastal areas worldwide, where climate-related threats, such as rising sea-levels and changing patterns, frequency and intensity of extreme events (e.g., coastal storms, floods; IPCC, 2021, 2023; MATTM, 2017), affect natural ecosystems and the communities (IPCC, 2021, 2023). Addressing these challenges requires a shift from traditional single hazard assessment to a multi-hazard and multi-risk framework, analysing the complexity and spatio-temporal overlapping nature of multi-risk events (De Angeli et al., 2022; Simpson et al., 2021; Ward et al., 2022; Zschau, 2017). This paradigm shift allows for a more comprehensive understanding of hazards, simplifying the development of targeted solutions to address multiple risks that coastal areas face. These interactions can intensify impacts, resulting in more severe outcomes, which requires holistic approaches that consider multi-hazard, multi-scale, and multi-sector perspectives (Claassen et al., 2023; Dal Barco, Maraschini, et al., 2024; Terzi et al., 2019; Zennaro et al., 2021).

Coastal local authorities and policymakers are increasingly faced with the challenging task of balancing coastal development with risk management. An integrated approach to assess multiple risks along coastal areas is needed to identify, on one hand, the main causes contributing to this rise of coastal risks and to identify, on the other hand, the most appropriate adaptation and risk management measures.

According to the framework developed within the H2020 MYRIAD-EU project (Hochrainer-Stigler et al., 2023), this study uses a multi-risk assessment approach and follows the international and European risk assessment guidelines for climate change adaptation and disaster risk reduction (EC, 2010, 2019; EEA, 2018; EUCRA, 2024; Poljansek et al., 2019; UNDRR, 2017) and the international ISO standard (ISO/IEC 31010:2019) to perform a scoping climate risk assessment at the regional to local scale. Risk assessment is used to facilitate a shared understanding of the risks affecting the Veneto region, as well as their relative significance (priority) in the context of both current (reference) and future scenarios. The identified, assessed and prioritized risks are then used as the basis for risk management planning and, therefore, the identification of risk reduction measures.

More specifically, the research activities in this study involved the identification and prioritization of the main climate-related hazards and risks affecting the coastal areas of the Veneto region, and followed the main phases of the standard ISO/IEC 31010:2019, i.e., *problem formulation*, *risk identification*, *risk analysis*, *risk evaluation* and *risk treatment*.

Furthermore, advances in Machine Learning (ML) and Artificial Intelligence (AI) in general have opened new possibilities for multi-risk assessment, exploiting vast data sources for environmental observation and monitoring (e.g., remote sensing data from Copernicus Sentinels, USGS Earth

Explorer; Castruccio & Genton, 2018; Fogarin et al., 2023; Pham et al., 2023, 2024). In particular, custom Large Language Models (LLMs), such as those based on OpenAI's Generative Pre-training Transformers (GPTs; OpenAI, 2023), have shown potential in analysing and synthesizing diverse data sources to create enhanced frameworks for multi-risk assessment and resilience building. These models operate as context-enhancing tools, leveraging extensive pre-training on vast datasets to provide nuanced insights across domains (Garrido-Merchán et al., 2023). Unlike other methods such as retrieval-augmented generation (RAG) or fine-tuning, custom GPTs allow to use a combination of prompt engineering and instruction tuning to align outputs with specific user needs, incorporating domain-specific knowledge uploaded on a size-limited vector database, without requiring extensive retraining (Schulhoff et al., 2024). This setup allows these tools to adapt flexibly to varied applications, including multi-risk assessment, where they synthesize information from sources such as scientific studies, historical data, and real-time inputs (Almasre, 2024; Garrido-Merchán et al., 2023).

This paper introduces COAST-AId (*COastal multi-risk Assessment SupporTed by AI-baseD tools*), a custom GPT-based tool designed to support multi-risk assessment and management in the Veneto coastal area, one of the climate change hotspots in the Mediterranean basin (Gallina et al., 2019; Torresan, Critto, Rizzi, & Marcomini, 2012). COAST-AId follows the approach proposed in the first European Climate Risk Assessment (EUCRA) report, which provides an evaluation of climate risks across Europe (EUCRA, 2024). The report identifies 36 major climate risks that threaten European critical sectors, including food, ecosystems, infrastructure, economy and finance, and health. Many of these risks have already reached critical levels and could escalate to catastrophic consequences without urgent and decisive action. The EUCRA approach includes four consecutive steps, i.e. (i) *risk identification*, (ii) *risk analysis*, (iii) *policy analysis*, and (iv) *urgency evaluation*.

In the *risk identification*, the major climate risks have been selected for the European regions through an initial screening of the relevant scientific literature, which followed the criteria adopted by the IPCC AR6 (e.g., high magnitude and likelihood of severe consequences, high irreversibility, potential cascading effects beyond system borders, worsening effect of climate change over time).

The *risk analysis* step assesses the severity of each major climate risk (classified as limited, substantial, critical, or catastrophic) across three timeframes (current, mid-century, or late century). Furthermore, the confidence level is determined based on the type, quantity, quality, and consistency of evidence, as well as the degree of agreement among the sources.

The *policy analysis* step evaluates temporal horizon, ownership and readiness of EU policies to examine the level of risk recognition and management.

Finally, the *urgency to act* is determined by combining the findings from the previous steps into a matrix, hereinafter referred as the "EUCRA matrix". The outcome considers five categories: watching in brief, sustain current action, further investigation, more action needed e urgent action needed. For more details on the classification of each level, refer to Annex 1.

COAST-AId is designed to support the application of the EUCRA approach to the regional (subnational) scale, rapidly delivering accessible and actionable information on key risks impacting the Veneto coastal area. This enables local policymakers and stakeholders to enhance their risk knowledge and foster adaptation strategies, paving the way for more effective and sustainable regional resilience planning. Therefore, following the EUCRA approach, COAST-AId supports three primary objectives: (i) identifying major risks for the Veneto coast – *risk identification*, (ii) analysing the severity of these risks – *risk analysis*, and (iii) evaluating current policies and adaptation strategies – *policy analysis*. Following the performance evaluation provided by local stakeholders and AI-experts, these outputs are incorporated into the EUCRA matrix applied to calculate the *urgency to act* for the identified major coastal risk within the Veneto region. This integration offers valuable insights to refine local policies and supports the development of a resilient coastal management plan aligned with the 2024 Regional Strategy for Climate Change Adaptation in the Veneto region (Regione del Veneto, 2024).

This paper explores the application of COAST-AId, carried out in close collaboration with local stakeholders. The tool represents a preliminary attempt to apply the EUCRA approach at a regional-to-local scale, with a specific focus on the Veneto coast (Section 5.25.2). Key outputs, including the stakeholders' evaluation of COAST-AId's performance, are discussed in Section 5.3.

## 5.2. Methodology

This study aims to support the prioritization of coastal risks and enhance adaptation and risk management strategies for coastal areas in the Veneto region, addressing climate change challenges through the application of a customized tool based on a pre-trained LLM, GPT4o (Hurst et al., 2024).

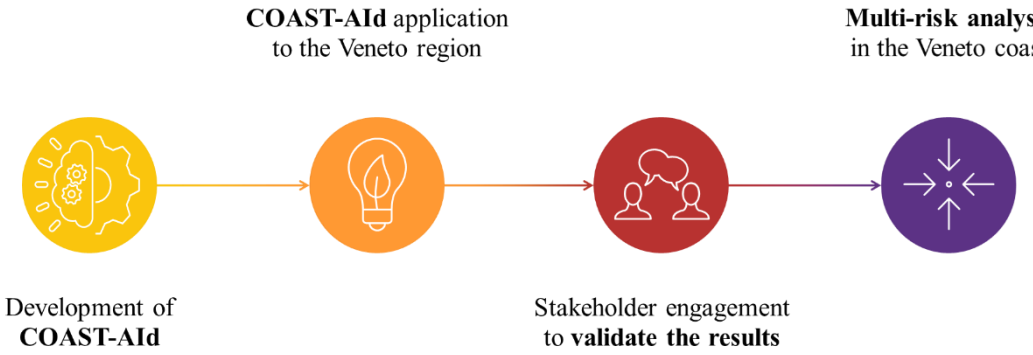



*Figure 21. Workflow adopted to prioritise risks and improve current adaptation strategies in the Veneto coast.*

The proposed methodology followed four steps, as depicted in Figure 21. Fist, COAST-AId's instructions and knowledge were designed and prepared (Section 5.2.1). Then, the tool was applied to the coastal areas of the Veneto region following the *European Climate Risk Assessment* (EUCRA) approach as a reference framework and methodological guide. This application was aimed to identify the region's most significant coastal risks, assess their severity, and evaluate current policy readiness to address these challenges (Section 5.2.2). To ensure the reliability of the results, AI experts and local stakeholders were actively engaged in evaluating COAST-AId's performance and outputs (Section 5.2.3). This validation was a crucial step towards achieving the overarching goal of determining the urgency of actions required to reduce the identified coastal risks (Section 5.2.4). The following sections provide a detailed description of each phase.

### *5.2.1. COAST-AId development*

The assessment of multiple risks within the complex system of the Veneto region's coastal area required the integration and analysis of a wide range of data sources, including reports, datasets, and documents. To address this challenge and extract the most relevant information for coastal risk assessment, a custom LLM called COAST-AId (*COastal multi-risk Assessment SupporTed by AI-baseD tools*, https://chatgpt.com/g/g-12xYfUHJh-coast-aid), was developed.

During its initial development, COAST-AId was built and tested using software layers based on GPT-4o. However, with the rapid evolution of underlying models, the tool continues to adapt to emerging advancements. COAST-AId leverages OpenAI's Generative Pre-trained Transformer (GPT), specifically ChatGPT-4o, to efficiently synthesize information and extract comprehensive insights from diverse input sources. The system operates through a structured integration of custom instructions (prompts) and curated knowledge, which are uploaded to OpenAI's vector database. When a user interacts with COAST-AId, the application retrieves relevant information from this database, ensuring contextually enriched responses. By incorporating custom instructions and domain-specific knowledge from uploaded documents, COAST-AId enhances its generative capabilities, providing more accurate and actionable insights.

Currently, the prototype tool is set to private mode, due to the inclusion of various non-open-source materials, such as subscription-based scientific papers and regional reports provided exclusively to the research team under specific agreements with the issuing authorities. To address this limitation, while ensuring transparency of the process and enabling replicability for other users, a detailed list of all documents used as input for the model has been included in Supplementary Material SM2. Additionally, the functionality allowing web-based information retrieval was disabled, allowing the authors complete control over the input data.

In the initial stages of the development, COAST-AId was tested using a subset of the 60 documents included in the final dataset. This approach allowed an iterative refinement of the tool's linguistic and contextual understanding. By starting with a smaller, curated selection of documents, the gaps in the LLM's comprehension of domain-specific language were identified, leading to significant improvements in the quality of its outputs. This phase concluded with the integration of advanced prompt design techniques, balancing technical expertise and creative intuition to enhance user interaction with the model. The authors adopted the prompt classification framework proposed by Schulhoff et al. (2024), employing the following techniques:

- *Few-Shot Prompting*, providing the model with a few examples to learn from, enabling the generation of contextually relevant and informed responses (Brown et al., 2020).
- *Chain-of-Thought Prompting*, encouraging the model to reason step-by-step through a problem, promoting logical reasoning and ensuring structured and accurate responses (Wei et al., 2022).
- *Role Prompting*, instructing the model to adopt the role of an expert (e.g., jurist, data analyst), ensuring methodological task execution within the context of that role (R. Wang et al., 2024).
- *Decomposition*, breaking down a complex task into smaller, manageable steps, allowing the model to address each part accurately (Khot et al., 2022).
- *Step-Back Prompting*, where the model reflects on broader implications, promoting deeper analysis and thoughtful conclusions (Zheng et al., 2023).
- *Zero-Shot Chain-of-Thought Prompting*, directing the model to provide step-by-step reasoning, guiding it to produce detailed and well-reasoned responses without prior examples (Kojima et al., 2022).

These prompting strategies were pivotal in fine-tuning the interaction between COAST-AId and the user, culminating in a refined set of prompts specifically designed to apply the EUCRA approach to the Veneto region's coast, as outlined in Section 5.3.1.

### *5.2.2. Application of COAST-AId to the Veneto region*

COAST-AId was created aiming to facilitate the application of the EUCRA approach to the local scale, making the complex data landscape of the Veneto coastal area more accessible to policymakers and stakeholders. The European approach includes four consecutive steps: *risk identification*, *risk analysis*, *policy analysis*, and *urgency to act*, which will be introduced in the following sections.

#### *5.2.2.1. Risk identification*

To support the identification of major climate risks (first level of the EUCRA approach, see Section 5.1) affecting the coastal area of the Veneto region, the input documents (detailed in Annex 2) were analysed and synthesised using the COAST-AId tool. The prompts specifically designed for this step aimed to generate a comprehensive understanding of the Veneto coastal system, encompassing both climatic and non-climatic drivers, as well as their interactions leading to the identified coastal risk. The final output of this step is a conceptual framework that provides a comprehensive overview of the Veneto coastal system, which will be presented in Section 5.3.2, and laying the foundation for the subsequent *risk analysis*, presented in Section 5.2.2.2.

#### *5.2.2.2. Risk analysis*

As outlined in Section 5.1, the second level of the EUCRA approach involves risk analysis, focusing on the assessment of both the severity of each identified major coastal risk and the corresponding confidence level. The classification for risk severity follows the EUCRA framework (i.e., limited, substantial, critical, catastrophic) across three distinct timeframes (i.e., current, mid-century, late century), as detailed in Annex 1. To assess the EUCRA-defined confidence level, the volume of information available for each major risk derived directly from the input documents of the COAST-AId tool was used as a proxy. This adjustment ensured that the assessment aligns with the data availability and context-specific characteristics of the Veneto region while maintaining methodological consistency with the overall risk analysis framework. In particular, the greater the quantity and relevance of the information, the higher the confidence level is assigned to that coastal risk, ensuring a tailored evaluation that accurately reflects the data's robustness. In particular, the confidence levels are categorised as follows: low if a maximum of five documents are identified, medium for six to ten documents, high for more than ten documents concerning the designated risk for the Veneto coast.

#### *5.2.2.3. Policy analysis*

Following the EUCRA approach outlined Section 5.1, the third level encompasses the analysis of current policies, including evaluations of risk ownership, policy horizon and policy readiness. As at the European level, where the 2021 EU adaptation strategy provides an overarching framework for adaptation policies, but implementation is mainly through sectoral policies (EUCRA, 2024), the Strategy for Climate Change Adaptation of the Veneto Region (i.e., *Strategia Regionale di Adattamento ai Cambiamenti Climatici per il Veneto* – SRACC; Regione del Veneto, 2024) sets strategic objectives to be implemented and/or being implemented within sectoral planning processes.

The SRACC itself provides a comprehensive list and preliminary analysis of existing plans that include a number of adaptation and risk reduction measures. For the purpose of this study, which focuses on the regional level and aims at supporting policy makers in Veneto, only policy and plans associated with regional ownership were processed by COAST-AId.
For the remining policy indicators (i.e., temporal horizon and policy readiness) the classification aligns with the EUCRA framework, reported in Annex 1.

### *5.2.3. Engaging experts and local stakeholder to evaluate COAST-AId performance*

The deployment of LLMs in real life settings is still in its infancy and it has been limited by challenges related to their reliability, the generation of hallucinations, and replicability in different contexts. To address these challenges, several frameworks have been developed to systematically assess LLM outputs, most of which rely on human evaluation (Cheung, 2024).
In this study, experts and local stakeholders were engaged during the MYRIAD-EU project workshop in which the COAST-AId tool and its outputs were presented. Following the presentation, participants were requested to evaluate the outputs and articulate their levels of agreement or disagreement through structured questionnaires and interviews. The evaluation was conducted based on recent frameworks commonly used for LLM benchmarking (Y. Chang et al., 2024; Kroll & Kraus, 2024; Tam et al., 2024), which identify five key criteria: accuracy, relevance, clarity, completeness and conciseness. *Accuracy* assesses whether the LLM's response is factually correct, aligned with verifiable data, or grounded in trusted external sources. In critical applications such as environmental risk management or financial services, incorrect information can lead to severe consequences. *Relevance* measures how well the response addresses the specific prompt. Outputs should be focused and aligned with the topic at hand (Cheung, 2024). For instance, when evaluating risks in the Veneto coastal area, responses must provide information pertinent to the location and associated hazards. *Clarity* refers to the ease with which the response can be understood by the user. A well-structured, easy-to-follow response ensures that even complex information is digestible. This is particularly important for decision-makers who need quick, actionable insights. *Completeness* ensures that all components of the prompt are addressed in the response. For multi-part questions or prompts requiring detailed lists (e.g., hazard identification, risk ownership), it is crucial that no critical information is omitted. *Conciseness* evaluates whether the LLM delivers the required information efficiently, without unnecessary verbosity. Responses should be brief yet comprehensive, avoiding excessive elaboration that may obscure important points.

The insights gained from these evaluations were synthesised into the final COAST-AId results, contributing comprehensive information on *risk identification*, *risk analysis*, and *policy analysis* for the Veneto coastal area, which will be detailed in Section 5.3.3.

### *5.2.4. Veneto coastal multi-risk assessment and management*

The last step of the EUCRA approach involves  determine the urgency and type of policy action (EUCRA, 2024).

When focusing on the coastal area of the Veneto region, the urgency to act was determined in two different ways. First, COAST-AId outputs from the previous steps were integrated into the EUCRA matrix. Then, COAST-AId was employed one final time to independently calculate the urgency to act. Both results - those calculated by the EUCRA matrix and those determined by COAST-AId - were categorised into five levels of urgency (i.e., watching in brief, sustain current action, further investigation, more action needed, and urgent action needed). More details on these categories are provided in Annex 1.

This approach enabled a comparative analysis of the results produced by the EUCRA matrix and COAST-AId, presented in Section 5.3.4.

## 5.3. Results and discussion

### *5.3.1. COAST-AId development*

The development of COAST-AId was a comprehensive and iterative process, culminating in the identification and refinement of the final set of prompts, reported in Table 8.

*Table 8. Final set of prompts used for applying the EUCRA approach to the coastal areas of the Veneto region.*

| EUCRA level | Prompts | Technique |
|---|---|---|
| Risk identification | *Previous assessments have identified sea-level rise as a significant climatic hazard and urban development as a non-climatic hazard responsible of the occurrence of coastal erosion risk in the Veneto coastal area. Considering this example, list the most important climatic (atmospheric, marine, and terrestrial) and non-climatic hazards responsible for each coastal risks in the Veneto coastal area.* | Few-Shot Prompting (Brown et al., 2020) |
| | *First, identify the most relevant coastal risks occurring along the Veneto coastal area. Next, for each risk, list the combinations of climatic and non-climatic hazards previously identified as the most important hazards responsible for these risks. Explain how these hazard combinations contribute to each specific risk in the coastal areas of the Veneto region.* | Decomposition (Khot et al., 2022) |
| Risk analysis | *As a data analyst, review each attached file and count the number of documents focused on each coastal risk identified so far for the Veneto coastal area. Provide a step-by-step summary of your counting process for each file.* | Role Prompting (R. Wang et al., 2024) |
| | *For each coastal risk identified so far for the Veneto coastal area, provide:*<br>• *the climatic and non-climatic hazards responsible for the risk.*<br>• *the level of severity (Catastrophic, Critical, Substantial, Limited – based on the European Climate Risk Assessment classification) for the current situation (until 2040), mid-century (2040–2060), and end of the century (until 2100).*<br>• *for each time frame, explain in detail the reasons for the assigned severity level, reasoning step-by-step.*<br>• *the measures implemented to address the risk.*<br>• *the sectors affected by this risk.* | Zero-Shot Chain-of-Thought Prompting (Kojima et al., 2022) |
| | *First, explain the rationale behind the management measures implemented for each coastal risk in the Veneto coastal area. Then, assess how these measures have either reduced or increased the impacts of the other risks, considering only the risks identified so far for the Veneto coastal area. Provide examples and explain why these effects occurred.* | Step-Back Prompting (Zheng et al., 2023) |

| EUCRA level | Prompts | Technique |
|---|---|---|
| Policy analysis | *Using the provided definition of 'policy horizon', determine the policy horizon along the Veneto coastal area related to each coastal risk identified so far for the Veneto coastal area as a consequence of climatic and non-climatic hazards. Explain your reasoning step-by-step, considering the severity of the risk over time.* | Chain-of-Thought Prompting (Wei et al., 2022) |
| | *As a policy analyst, identify the policies issued by at the sub-national/local scale of the Veneto region that cover each coastal risk identified so far for the Veneto coastal area. Provide brief descriptions of each policy and explain how they address each Veneto coastal risk.* | Role Prompting (R. Wang et al., 2024) |
| | *Using the provided categories of 'policy readiness', evaluate the norms and policies related to each coastal risk identified so far for the coastal area of the Veneto region. Explain your reasoning step-by-step to determine whether the policy readiness is Low, Medium, Advanced, or Very Advanced.* | Chain-of-Thought Prompting (Wei et al., 2022) |
| Urgency to act | *First, summarize the information related to 'risk severity', 'confidence', 'policy horizon', and 'policy readiness' for each coastal risk identified so far for the Veneto coastal area. Next, using the European Climate Risk Assessment classification, identify the appropriate class of 'urgency to act' (i.e., 'urgent act needed', 'more action needed', 'further investigation', 'sustain current action', 'watching brief'). Explain your reasoning step-by-step.* | Decomposition (Khot et al., 2022) |

The initial application of the tool revealed challenges related to hallucinations, which were effectively mitigated through structured prompting techniques (outlined in Section 5.2.1) and multiple rounds of refinement. These improvements significantly enhanced the reliability and accuracy of responses, ensuring that the tool's outputs aligned more closely with the input data and were more applicable for decision-making processes.

A crucial factor in strengthening COAST-AId's reliability was its co-development with local stakeholders, whose in-depth knowledge of territorial characteristics, challenges, and needs proved invaluable. Their expertise, as discussed in Section 5.3.3, played a pivotal role in refining the tool's functionality, ensuring that the generated insights were both contextually relevant and scientifically sound.

Given that LLMs are still in the early stages of their application, adopting structured prompting techniques and actively involving domain experts in the validation process remains essential. While these tools can streamline and expedite desk reviews, their inherent limitations must be acknowledged. Therefore, the iterative refinement of AI-assisted tools, such as COAST-AId, combined with expert engagement, ensures they serve as valuable instruments for analysing complex, multi-dimensional risks while maintaining scientific rigor.

### *5.3.2. Application of COAST-AId to the Veneto region*

The proposed study aims to apply the EUCRA approach to the local context of the Veneto coast, harnessing the capabilities of the COAST-AId tool. The following sections provide a comprehensive breakdown of the outcomes from each step of the EUCRA approach (detailed in Section 5.2.2). In particular, Section 5.3.2.1 covers risk identification, risk analysis is discussed in Section 5.3.2.2, and finally policy analysis is presented in Section 5.3.2.3.

*5.3.2.1. Risk identification*

COAST-AId was employed to identify the major climate risks impacting the coastal area of the Veneto region, through a set of specific risk related prompts, encouraging the retrieval of relevant information from the documents available in the tool. This application provided a comprehensive understanding of the Veneto coastal system, culminating in the development of the conceptual framework presented in Figure 22.

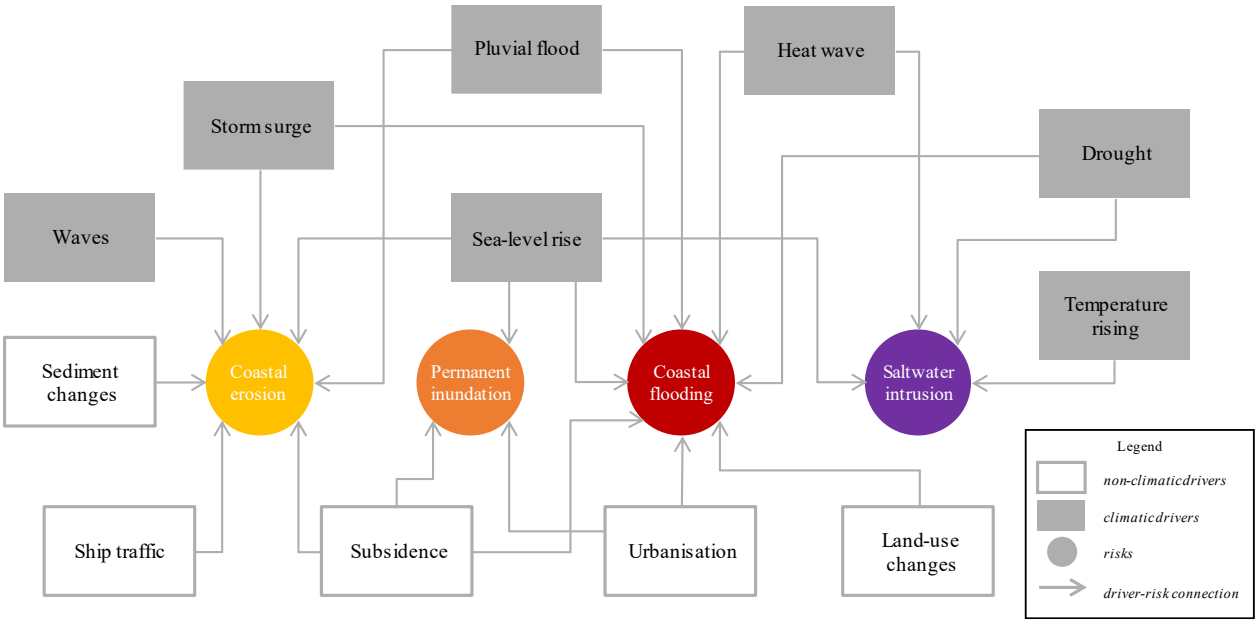



*Figure 22. Conceptual framework for coastal risk assessment in the Veneto region (Italy).*

The conceptual framework illustrates the interplay between climatic-related hazards and non-climatic risk drivers, which together shape the major climate-related risks identified in the case study.

Coastal erosion is driven by an intricate combination of climate-related hazards, including storm surge, sea-level rise, and pluvial flooding (Pham et al., 2024). These hazards, exacerbated by the increasing frequency of extreme weather events observed over recent decades (Dal Barco, Maraschini, et al., 2024) and projected to intensify in the future (Dal Barco et al., 2025), collectively reshape shorelines, redistribute sediments, and destabilize coastal ecosystems (Fogarin, Zanetti, Dal Barco, et al., 2023). When these hazards interact, their impacts often reveal the compounding nature of extreme events (Dal Barco, Maraschini, et al., 2024). For instance, sea-level rise amplifies the effects of storm surges and wave impacts, whereas the combination of pluvial flooding and storm surge-induced coastal inundation accelerates sediment displacement and erosion (Barbi et al., 2012; Fogarin, Zanetti, Dal Barco, et al., 2023).

Non-climatic risk drivers, such as sediment changes, shipping traffic and subsidence, further exacerbate this unstable situation by disrupting the physical processes that regulate sediment dynamics and shoreline stability. Although not directly linked to climate change, these factors (such as land subsidence and anthropogenic pressures) significantly increase the susceptibility of coastal system to climatic hazards like wave action and storm events (Gallina et al., 2020; Sambo et al., 2023). The combined effects of subsidence and sea-level rise are particularly concerning, as they increase relative sea-level changes and heighten the risk of coastal flooding and permanent inundation (Falciano et al., 2023; Ferrarin et al., 2022). This dynamic is especially pronounced in the Veneto region, characterised by low-lying topography prone to flooding (Antonioli et al., 2017; Barbi et al., 2012; Scorzini & Frank, 2015), dense coastal development that amplifies exposure (Gallina et al., 2020; Sambo et al., 2023), and reliance on artificial water management systems (e.g., MOSE system), which face escalating challenges from these rising hazards (Cavaleri et al., 2020; Faranda et al., 2023). Saltwater intrusion arises from a feedback loop involving subsidence, rising sea-levels and temperatures, drought, and heatwaves, all of which amplify coastal risks (Luo et al., 2024; Tosi et al., 2022). Subsidence reduces land elevation, increasing vulnerability to saltwater intrusion during droughts and heat waves. Concurrently, rising temperatures and heat waves diminish freshwater availability, weakening natural hydrological defences (Bellafiore et al., 2021; Bonaldo et al., 2023; Tosi et al., 2022). Human activities, such as excessive groundwater extraction for irrigation and urban development, further exacerbate these risks by intensifying subsidence and depleting freshwater reserves (Beretta & Terrenghi, 2017; Tarolli et al., 2023).

*5.3.2.2. Risk analysis*

Following the identification of the major risks affecting the coastal area of the Veneto region (i.e., coastal erosion, permanent flooding, coastal flooding, and saltwater intrusion), the COAST-AId tool was employed to conduct a detailed risk analysis through a set of specific prompts to retrieve the relevant information from the documents available in the tool. This analysis assessed both the severity of each coastal risk, and the confidence level associated with the supporting documentation. The resulting matrix (Table 9) offers a clear visual representation of the methodology detailed in Section 5.2.2.2. It enables the understanding and effective prioritisation of the intensifying risks affecting the Veneto coast, while capturing the temporal evolution of these risks across current, mid-term, and long-term scenarios.

*Table 9. COAST-AId outputs related to risk analysis, which includes risk severity across three different temporal timeframes (current, mid-term, long-term) and the confidence level for the Veneto coastal area.*

| **Risks** | **Risk severity** | | | **Confidence level** |
|---|---|---|---|---|
| | *Current* | *Mid-term* | *Long-term* | |
| Coastal erosion | Substantial | Critical | Catastrophic | ++ |
| Permanent inundation | Limited | Substantial | Critical | + |
| Coastal flooding | Substantial | Critical | Catastrophic | +++ |
| Saltwater intrusion | Limited | Substantial | Critical | + |

Coastal erosion, driven by rising sea levels, storm surges, and reduced by beach nourishment and dune restoration efforts (Fogarin, Zanetti, Dal Barco, et al., 2023; Pham et al., 2024), currently poses a *Substantial* risk. However, mid-term classification indicates an escalation to *Critical*, fuelled by accelerating sea-level rise and increasing storm intensity (Pham et al., 2023). In the long term, unchecked erosion could lead to *Catastrophic* consequences for coastal infrastructure, ecosystems, and local communities. These findings align with regional studies, which emphasise the compounded impacts of geomorphological vulnerabilities and anthropogenic pressures, such as urbanization and tourism development (Fontolan et al., 2014; Marsico et al., 2017; Van Der Borg, 1992).

A similar pattern is observed for coastal flooding, exacerbated by the Veneto coast's peculiar geomorphology, characterized by low-lying littoral zones (Bezzi et al., 2018; Ruol et al., 2018). The situation is further strained by the existing flood defence infrastructures (e.g., MOSE system) which may require substantial upgrades to address the growing magnitude and frequency of extreme weather events (Anzidei et al., 2024; Faranda et al., 2023; Lionello et al., 2020).

The interplay of sea-level rise and land subsidence are making the Veneto coast increasingly vulnerable to permanent inundation (Falciano et al., 2023; Ferrarin et al., 2022). While currently classified as a *Limited* risk, this coastal risk is projected to become *Substantial* in the mid-term and *Critical* in the long-term, particularly under high-emission scenarios such as RCP8.5 (Falciano et al., 2023; Pham et al., 2023).

Similarly, saltwater intrusion, currently set as a *Limited* risk, is projected to intensify as rising sea levels diminish freshwater flow (Beretta & Terrenghi, 2017; Tarolli et al., 2023). Mid-term and long-term scenarios elevate this risk to *Substantial* and *Critical*, respectively, posing significant threats to agriculture and freshwater availability, underscoring the need for proactive water management strategies to limit this risk (Abd-Elaty et al., 2021).

Finally, as detailed in Section 5.2.2.2, the confidence level was directly derived from the input documents of the COAST-AId tool, serving as a reliable proxy of the EUCRA-defined confidence level. Specifically, COAST-AId quantified the number of documents associated with each risk

identified in Section 5.3.2.1. The analysis revealed that coastal flooding had the highest number of related documents (16), followed by coastal erosion (10) and permanent inundation (5). Saltwater intrusion had the lowest level of documentation (4), reflecting a relatively recent – but growing – concern within the scientific community.

### *5.3.2.3. Policy analysis*

Major coastal risks identified for the Veneto region include coastal erosion, coastal flooding, permanent inundation, and saltwater intrusion, driven by both climatic and non-cimatic factors.
To conduct a preliminary assessment of existing regional policies, strategies, and plans, the COAST-AId tool was employed through a set of specific prompts to retrieve relevant information with the aim of applying the EUCRA approach (EUCRA, 2024) to the Veneto coast. The policy analysis followed the EUCRA methodology, thus assessing *risk ownership*, *policy horizon*, and *policy readiness*, as illustrated in Table 10. The analysis considered all sectoral plans included in the SRACC, through which the Veneto Region intends to achieve strategic objectives to foster transformative adaptation.

*Table 10. Resulting output of the COAST-AId tool for what concerns the policy analysis, which includes policy ownership, temporal horizon and policy readiness for the Veneto coastal area.*

| **Risks** | **Risk ownership** | **Policy horizon** | **Policy readiness** |
|---|---|---|---|
| Coastal erosion | Veneto | Mid- to Long-term | Medium |
| Permanent inundation | Veneto | Long-term | Medium |
| Coastal flooding | Veneto | Long-term | Advanced |
| Saltwater intrusion | Veneto | Mid- to Long-term | Medium |

The assessment of policy readiness reveals varying levels of maturity across the different risks. Coastal erosion and saltwater intrusion policies are categorized as having a *medium* level of readiness, reflecting ongoing efforts to develop both grey and nature-based solutions, such as dune restoration and sediment management (Del Vecchio et al., 2022; Fontolan et al., 2014). Similarly, readiness for permanent inundation is also rated as *medium*, with efforts focused on enhancing spatial planning, restoring floodplains, and strengthening critical infrastructure (Faranda et al., 2023). In contrast, policies addressing coastal flooding demonstrate an *advanced* level of readiness, bolstered by the MOSE system, which has significantly enhanced the region's capacity to manage storm surges and extreme flooding events (Lionello et al., 2021).

Overall, the policy readiness assessment shows positive results across the identified major risks, proving that several risk reduction measures have been planned and implemented in Veneto over the past decades to address coastal risks (Fontolan et al., 2014). However, these measures have often been designed with a single-risk focus, overlooking that risk management measures targeting one risk can create synergies or a-synergies with other risks (Ward et al., 2022). For instance, coastal infrastructure, such as groins and breakwaters, has been built to protect and stabilise the coastline (Ferrarin et al., 2020; Fogarin, Zanetti, Dal Barco, et al., 2023). While effective in localised contexts, these structures often disrupt the natural southward sediment drift, affecting coastal dynamics and introducing unintended consequences (Fontolan et al., 2007).

Although the recently published Strategy for Climate Change Adaptation in the Veneto Region (i.e., *Strategia Regionale di Adattamento ai Cambiamenti Climatici per il Veneto* – SRACC; Regione del Veneto, 2024) represents a significant step towards transformative adaptation, the analysis conducted shows that a single-risk approach is still in place and that further effort is needed to achieve a holistic perspective in coastal risk management. Future revisions of the Strategy represent an excellent opportunity to implement a paradigm shift in coastal risk governance by fostering a multi-risk framework, thus abandoning a siloed approach in both risk assessment and management. Incorporating mechanisms to assess and manage cascading effects would improve the strategy's robustness and align with the most recent international best practices in disaster risk management and climate adaptation (IPCC, 2023; Simpson et al., 2021).

The COAST-AId tool was also used to evaluate the temporal horizons of the SRACC sectoral plans for addressing the major costal risks in the Veneto region. Temporal horizons refer to the timeframe required for plans, strategies, and policies to become effective in reducing risks, influenced by the lead time of adaptation actions and the lifespan of current adaptation decisions (Section 5.2.2.3). The tool highlighted that policies for coastal erosion and saltwater intrusion will achieve efficacy in the mid- to long-term timeframe, while policies for permanent inundation and coastal flooding require a long-term horizon.

The long-term horizon for coastal flooding policies is surprising, considering the urgency of the issue in the region and the various plans and measures already in action. In particular, following severe floods across Europe between 1998 and 2004, an European Floods Directive (Dir.2007/60/EC) was introduced to mandate comprehensive flood risk management. This directive requires an integrated approach combining prevention, protection, and preparedness measures, including flood forecasting and alert systems, addressing both land management and regional civil protection. Conversely, the medium-to-long-term horizon assigned to saltwater intrusion policies is unexpected, as this coastal risk has only recently gained attention and remains under-investigated.

To address these observations, the insights were discussed with local stakeholders to refine the inputs for EUCRA matrix application (Section 5.3.3). The results of this application will be presented and analysed in Section 5.3.4, aimed to define the urgency levels for each major coastal risk in the Veneto region. This process seeks to provide valuable support to decision-makers in identifying necessary improvements to current plans, strategies, and policies.

### *5.3.3. Engaging experts and local stakeholder to evaluate COAST-AId performance*

To evaluate COAST-AId results discussed in the previous sections, experts and local stakeholders were engaged during the MYRIAD-EU project workshop in which the COAST-AId tool and its outputs were presented. As detailed in Section 5.2.3, the assessment was conducted based on five key criteria (i.e., accuracy, relevance, clarity, completeness and conciseness), whose outputs have been collected in Annex 3.

The *accuracy* evaluation of COAST-AId was conducted with the active participation of local stakeholders through a structured process involving a questionnaire followed by one-to-one interviews. These stakeholders, representing both public and private local authorities, provided invaluable insights into the Veneto region's territorial context. In particular, the stakeholders included representatives from four different Units of the Veneto Region (i.e., Environment and Ecological Transition, Territorial Protection and Safety, Soil and Coastal Defense, and Civil Protection), the Environmental Protection Agency of the Veneto Region, and Viveracqua Consortium, which encompasses companies managing water resources in the area. This diverse composition of stakeholders ensured a comprehensive range of perspectives, enriching the evaluation process and fostering a more robust discussion.

The overall accuracy of COAST-AId was deemed satisfactory, with stakeholders positively evaluating its performance. However, *saltwater intrusion* emerged as a notable exception (Table 11), with the risk severity being underestimated by the custom LLM. During the dialogue with the stakeholders, it became evident that the current and future severity level of saltwater intrusion should be revised. Stakeholders highlighted that the risk should be elevated from *limited* to *substantial* in the current period, from *substantial* to *critical* for the mid-term period, and from *critical* to *catastrophic* by the end of the century. Their feedback was further corroborated by additional documentation provided during the interviews, which not only supported the need for revised severity levels but also enhanced the confidence level associated with this specific coastal risk. The evaluation also revealed shortcomings in the policy readiness for addressing saltwater intrusion. Stakeholders emphasized that existing regional plans are insufficient to mitigate this risk effectively. Unless significant

interventions are made, the region's capacity to address saltwater intrusion would remain limited, with meaningful policy readiness unlikely to materialise before the end of the century.

*Table 11. Summary of risk analysis and policy analysis after the stakeholders' inputs.*

| **Risks** | **Risk severity** | | | **Confidence level** | **Policy ownership** | **Temporal horizon** | **Policy readiness** |
|---|---|---|---|---|---|---|---|
| | *Current* | *Mid-term* | *Long-term* | | | | |
| Coastal erosion | Substantial | Critical | Catastrophic | ++ | Veneto | M – L | Medium |
| Permanent inundation | Limited | Substantial | Critical | + | Veneto | L | Medium |
| Coastal flooding | Substantial | Critical | Catastrophic | +++ | Veneto | M - L | Advanced |
| Saltwater intrusion | Substantial | Critical | Catastrophic | ++ | Veneto | L | Medium |

This finding underscores the need for targeted policy development and implementation to address this escalating threat, which will be discussed in Section 5.3.4.

Furthermore, a panel of six AI experts, from the environmental and informatics departments of universities and research centres, was convened to assess the performance of the COAST-AId tool based on the remaining four key evaluation criteria: relevance, clarity, completeness, and conciseness. These experts provided comprehensive feedback, highlighting the tool's capability to generate responses that are contextually pertinent, well-articulated, and thorough while maintaining a concise format. Overall, their evaluation was positive, underscoring the significant potential of COAST-AId to advance multi-risk assessment frameworks. As detailed in Annex 3, the criteria of relevance, clarity, and conciseness received the highest ratings (i.e., high to very high). However, the completeness criterion garnered some medium to low score, particularly in the context of policy analysis. This highlights an area for further refinement, suggesting that future iterations of the tool should focus on improving its ability to provide more comprehensive insights when addressing complex policy-related challenges, thereby ensuring an even greater impact in its application.

### *5.3.4. Veneto coastal multi-risk assessment and management*

The final stage of the coastal risk assessment for the Veneto region focused on determining the levels of *urgency to act* required to address the identified risks. The results, summarised in Table 12, provide a comprehensive framework incorporating findings from two methodologies: *(i)* the final application of COAST-AId, and *(ii)* the EUCRA matrix calculations, which enable a direct comparison of the results from both methods.

*Table 12. Resulting output of the multi-risk assessment for the Veneto coastal area, including both applications - i.e., COAST-AId and the adapted EUCRA matrix for the Veneto case study.*

| Risks | Urgency to act (COAST-AId tool) | Urgency to act (EUCRA matrix) |
|---|---|---|
| Coastal erosion | **More action needed** | **Urgent action needed** |
| Permanent inundation | **More action needed** | **More action needed** |
| Coastal flooding | **Urgent action needed** | **More action needed** |
| Saltwater intrusion | **More action needed** | **Urgent action needed** |

The COAST-AId tool was employed to generate a final prompt assessing the urgency to act, drawing on information extracted from the input documents. This tool demonstrates significant potential by facilitating the analysis and synthesis of complex information, while providing practical recommendations for decision-making processes. Its ability to streamline data review and interpretation significantly reduces the time required for these tasks (Thulke et al., 2024). In particular, the integration of LLM-based tools like COAST-AId offers considerable advantages in processing and analysing large volumes of information (Kalla et al., 2023). This feature is especially critical for multi-risk assessments in well-documented case studies, such as the Veneto region, where diverse datasets and reports need to be carefully considered (Annex 2).

Furthermore, the flexible design of COAST-AId ensures its adaptability to other case studies with similarly extensive documentation. Such tool holds transformative potential for addressing complex, multi-dimensional challenges in coastal risk management, paving the way for more efficient and effective adaptation strategies (Vaghefi et al., 2023).

However, it is important to note that COAST-AId's performance is strictly dependent on the quality and comprehensiveness of the input documents, selected by the authors. This selection process was refined only after discussions with the local stakeholders, as detailed in Section 5.3.3. A comparison of findings between COAST-AId and the EUCRA approach (Table 12) reveals notable discrepancies. Despite these differences, both approaches highlight the urgency of prioritising the identified coastal risks. When the EUCRA matrix was applied to the coastal area of the Veneto region (Table 13) the results were further evaluated by local stakeholders. This collaborative evaluation process enhances the reliability of the outcomes.

*Table 13. EUCRA matrix integrating the classification for each assessment level (i.e., risk identification, risk analysis, policy analysis, and urgency to act) to evaluate and prioritise major coastal risks in the Veneto region.*

| **Veneto major coastal risks** | | **Coastal erosion** | **Permanent inundation** | **Coastal flooding** | **Saltwater intrusion** |
|---|---|---|---|---|---|
| ***Urgency to act*** | | ***Urgent action needed*** | ***More action needed*** | ***More action needed*** | ***Urgent action needed*** |
| Confidence | | Medium | Low | High | Medium |
| Risk severity | Current | Substantial | Limited | Substantial | Substantial |
| | Mid-century | Critical | Substantial | Critical | Critical |
| | End-century | Catastrophic | Critical | Catastrophic | Catastrophic |
| Policy analysis | Ownership | Regional | Regional | Regional | Regional |
| | Readiness | Medium-low | Medium-low | High | Medium-low |
| | Horizon | Medium-term | Long-term | Long-term | Long-term |
| Urgency - single period | Near-term | More action needed | Watching in brief | Sustain current action | More action needed |
| | Mid-term | Urgent action needed | Further investigation | Sustain current action | Urgent action needed |
| | Long-term | Urgent action needed | More action needed | More action needed | Urgent action needed |

The final urgency level was calculated by integrating information from the three previous levels of coastal risk assessment (i.e., risk identification, risk analysis, and policy analysis). The COAST-AId tool's outputs, combined with stakeholder evaluations, were used to populate the EUCRA matrix. This matrix integrates scores for key indicators, including risk severity, confidence, policy ownership, policy readiness, and policy temporal horizon, to determine the urgency level for each major coastal risk. The ultimate urgency levels, derived through the EUCRA matrix, provide a structured and actionable framework for addressing coastal risks in the Veneto region.

Coastal flooding is acknowledged as a critical issue by local stakeholders due to its profound impacts on livelihoods, tourism, and economic activities. Efforts to address this risk have been bolstered by the MOSE system, a sophisticated flood barrier activated in October 2020, which has significantly reduced flooding-related damages in Venice (Anzidei et al., 2024; Faranda et al., 2023). Despite these successes, projections suggest that the MOSE system may face limitations under high-emission scenarios by the end of the century. These include the possibility of prolonged gate closures, increased financial and ecological losses, and the eventual inadequacy of gate heights to counteract rising water levels (Lionello et al., 2021; Reimann et al., 2018; Tomasicchio et al., 2022). Such projections underscore the need for additional, long-term strategies to complement existing measures. These include integrating adaptive engineering solutions, refining policy frameworks, and fostering

community engagement to ensure sustainable protection for Venice and surrounding areas against the escalating threat of coastal flooding and potential permanent inundation.

Coastal erosion is closely monitored by the Veneto Region authority, which plays a central role in planning and implementing protective measures. Activities such as dredging river mouths, rehabilitating coastal zones, and constructing structural infrastructures like groins and breakwaters have been critical in mitigating erosion (Fogarin, Zanetti, Dal Barco, et al., 2023; Fontolan et al., 2014). However, these interventions have altered natural shoreline dynamics, creating zones of both accretion and erosion.

Beach nourishment efforts, involving the extraction of millions of cubic meters of sand, play a pivotal role in preparing the Veneto coastline for tourism, particularly after extreme storm surges. However, as the frequency and intensity of these events are projected to rise (Dal Barco et al., 2025), current plans require urgent updates to maintain the coastline's resilience and economic viability. Adaptive measures should focus on enhancing the sustainability of nourishment practices and integrating nature-based solutions to balance ecological and economic priorities.

Saltwater intrusion poses an escalating risk to coastal agriculture in the Veneto region, leading to soil degradation and crop damage (Hernández-Delgado, 2015; Tarolli et al., 2023). The freshwater-saltwater boundary has retreated significantly inland in recent years, exacerbated by rising sea levels, decreased freshwater input, and prolonged drought conditions (Antonellini et al., 2008; Da Lio et al., 2015; Lovrinović et al., 2021). While past reclamation efforts have provided temporary relief, long-term strategies remain absent. To address this risk, policymakers must implement robust measures such as constructing artificial barriers to limit saltwater encroachment, developing freshwater channels to counteract salinization, and strategically realigning agricultural boundaries (Luo et al., 2024; Nazarnia et al., 2020). These actions are critical to preserving agricultural productivity and environmental integrity in the region (Tarolli et al., 2023).

Through comprehensive planning and collaborative action, the Veneto region could strengthen its resilience to climate change impacts, setting a precedent for other coastal areas facing similar challenges. This approach will not only mitigate immediate risks, but also ensure long-term sustainability for the environment, economy, and communities in the region. In particular, the discrepancies between COAST-AId and the EUCRA matrix underscore the importance of combining data-driven assessments with stakeholder inputs to achieve comprehensive risk prioritization. More specifically, plans must prioritise:

1. long-term resilience, by developing adaptation and risk reduction strategies that account for projected changes in climate and sea levels, but also environmental and socio-economic changes. This approach ensures the longevity and effectiveness of protective measures.

2. capacity building, which could offer stakeholders, communities, and authorities the knowledge, tools, and collaborative frameworks needed to implement sustainable solutions (Giannini et al., 2016; O'Leary et al., 2024; Šakić Trogrlić et al., 2024).
3. integrated approaches, by fostering synergy between engineering solutions, policy development, and community engagement to address risks effectively.
4. establishment robust monitoring systems to evaluate the effectiveness of implemented measures and adapt strategies as conditions evolve (Tarolli et al., 2023).

## 5.4. Conclusion

This study was aimed at developing and implementing COAST-AId (*COastal multi-risk Assessment SupporTed by AI-baseD tools*), an innovative AI tool that leverages advances in Large Language Models (LLMs), to assess coastal risks and evaluate adaptation strategies in the Veneto region. By applying the European Climate Risk Assessment (EUCRA) approach to the specific challenges of the Veneto coastal area, COAST-AId successfully develop a comprehensive multi-risk assessment framework that aligns with European and international guidelines.

The results highlight the tool's ability to process extensive and heterogeneous data sources, such as scientific studies and policy documents, to generate actionable insights. The integration of LLMs allowed for the analysis and synthesis of complex information, facilitating policymakers in the identification of major risks that needs to be urgently addressed to effectively strengthen resilience. Furthermore, COAST-AId's adaptability and capacity to integrate new datasets ensure its continued relevance, making it a dynamic tool for addressing the evolving challenges of climate change.

Despite these achievements, several challenges were encountered. The reliance on local data highlighted the importance of well-curated and comprehensive information, underscoring the need for a robust repository of supplementary materials to facilitate replication in other regions. Stakeholder engagement revealed occasional misalignments between the tool's outputs and user expectations, demonstrating the necessity of context-sensitive calibration. Additionally, during the initial phases of application, occasional LLM hallucinations required manual verification to ensure accuracy, highlighting an area for future improvement to enhance reliability and user trust.

This study identifies significant opportunities for the further development and expansion of COAST-AId. Extending its applicability to other coastal and non-coastal regions offers promising potential, provided the tool is applied to local contexts. Moreover, developing an independent, open-access chatbot could enhance accessibility and usability for local communities, empowering users with a user-friendly interface to better understand and address risks.

To conclude, COAST-AId represents a systematic experimental tool that integrates the EUCRA framework at the regional (subnational) and local scales, specifically in the Veneto coastal area. The approach effectively bridges the gap between scientific analysis and actionable policy, providing a valuable resource for enhancing and developing coastal adaptation plans. While challenges remain, this study underscores the potential of custom LLMs in advancing sustainable and resilient coastal management, laying a foundation for future innovations in risk assessment and adaptation planning through AI-driven solutions.

# Chapter 6. *Conclusions*

This research explored the critical intersection of risk assessment and management, climate change, and Artificial Intelligence (AI) in coastal areas, with a particular focus on the Veneto region. Coastal zones, located at the dynamic land-sea interface, serve as vital sentinels of climate change due to their unique interplay of atmospheric, marine, and terrestrial systems. The Mediterranean Sea, in particular, is recognised as a global climate change hotspot, where the convergence of environmental stressors magnifies the vulnerability of its coastal ecosystems and communities. The complexity of these regions presents significant challenges for modelling and risk analysis, which requires innovative scientific approaches and actionable insights to support decision- and policymakers in designing and implementing effective adaptation and mitigation strategies.

In this context, the thesis addresses three main research questions: (*i*) *which are the main drivers of coastal risks along the municipalities of the Veneto region that can be identified through the implementation of Machine Learning algorithms*? (First Paper), (*ii*) *how accurately can AI methods estimate the frequency of future extreme weather events in the coastal municipalities of the Veneto region, based on historical and climate data*? (Second Paper) and lastly, (*iii*) *how can Large Language Models assist in enhancing climate adaptation strategies for coastal communities in the Veneto region, considering the multiple risks they face*? (Third Paper).
The investigation of these questions brought out significant insights, offering valuable reflections on the implementation of AI-based methodologies for coastal risk assessment and the enhancement of climate adaptation strategies.

The first consideration concerns the scientific relevance and innovative contribution of the research. For the first time, AI methodologies were employed to assess, predict, and manage coastal risks arising from extreme weather events in the Veneto region. The research introduced novel tools that expand the boundaries of AI applications in environmental science and climate change adaptation. In particular, these include:

- Machine Learning (ML) algorithms designed to estimate daily risk scores and identify the main drivers of Veneto coastal risks.
- A two-tier methodology for quantifying the future occurrence of impacts, which combines AI-driven risk assessment with mid- and long-term climate change scenario analysis.

- The development of COAST-AId (*COastal multi-risk Assessment SupporTed by AI-baseD tools*), a custom Large Language Model (LLM) designed to prioritise coastal risks and enhance current regional adaptation strategies.

These advancements represent a significant leap forward in integrating AI into climate risk assessment and adaptation planning. By bridging the gap between scientific research and actionable policy, these tools empower stakeholders with evidence-based tools to anticipate and mitigate the impacts of climate change. Beyond improving the understanding of complex coastal dynamics, the methodologies also illustrate the transformative potential of AI in addressing urgent challenges of climate resilience and sustainable coastal management.

Adaptability, robustness, and explainability of the developed applications are significant strengths of this thesis. The ML algorithms consistently demonstrated reliable performance across diverse datasets, highlighting their potential for application in other geographic regions and thematic contexts. Their modular design ensures flexibility, enabling a smooth integration with different data inputs and scenarios. Similarly, COAST-AId combined innovation of AI technologies with a practical framework, facilitating meaningful stakeholder engagement and informed decision-making. Collectively, these tools provide a detailed understanding of the complex interplay between hazards, vulnerabilities, and exposure offering a robust foundation for targeted mitigation and adaptation strategies.

Despite these strengths, the applications faced notable limitations, primarily related to the quality and availability of data. The scarcity and inaccuracy of impact datasets posed significant challenges, limiting the precision of the models. For instance, the exact location, magnitude, and type of impacts were often unavailable, limiting a comprehensive analysis of local vulnerabilities and exposure factors. Additionally, occasional inaccuracies in AI outputs, particularly within the implementation of LLM-based components in COAST-AId, required manual verification, underscoring the need for algorithm refinement and improved data curation, to enhance reliability and scalability of such tools.

Building on these findings, several avenues for future development are envisioned. Key recommendations include the creation of standardized and high-quality impact datasets through collaborative efforts between researchers, policymakers, and local authorities, which could further strengthen the applications and extend their utility in diverse contexts. Moreover, advancements in data collection technologies, leveraging innovations such as remote sensing and unstructured text mining, could further enrich the input datasets. Concerning the approaches implemented, expanding

the methodological framework incorporating more sophisticated AI tools, such as Recurrent Neural Networks or Graph Neural Networks, could enhance the analysis of spatial and temporal dependencies. Furthermore, embedding adaptation strategies within the assessment frameworks would enable sensitivity analyses of their effectiveness, fostering iterative improvements in planning. Finally, expanding COAST-AId for application in other regions and developing user-friendly interfaces, such as open-access chatbots, could facilitate broader stakeholder engagement and usability.

This Thesis underscores the transformative potential of AI in tackling complex environmental challenges. By advancing methodologies for coastal risk assessment and enhancing adaptation strategies, it contributes meaningfully to global efforts in climate change mitigation and resilience building. While challenges remain, the research lays a robust foundation for continued innovation in multi-risk assessment and adaptive management, providing tools to navigate a changing climate.

# Annexes

## Annex 1

*European Climate Risk Assessment approach: definitions and classification of the categories for each risk assessment level included in the first EUCRA report (EUCRA, 2024).*

*Risk analysis*

| Risk severity | Description |
|---|---|
| **Limited** | Limited or rare losses, no significant disturbance of system functionality. |
| **Substantial** | Substantial losses, moderate extent or pervasiveness, temporary or moderate disturbance of system functionality. |
| **Critical** | Large and frequent damage, large extent and high pervasiveness, long-term disturbance of system functionality, cascading effects beyond system boundaries. |
| **Catastrophic** | Very large and frequent damage, very large extent or very high pervasiveness, irreversible loss of system functionality, systemic risk. |

*Policy analysis*

- Temporal horizon
  - **short** – until 2040
  - **medium** – until 2060
  - **long** – until 2100

- Risk ownership
  European, national, co-owned

- Policy readiness
  - **low** – few, if any, policies, plans or strategies are in place to reduce the risk
  - **medium** – policies, plans, strategies or legislation are in place, but their targets and objectives are vague, or only short-term actions are considered
  - **advanced** – policies, plans or strategies that manage the risk effectively are partly in place
  - **very advanced** – policies, plans or strategies are in place with clear objectives and actions to manage the risk

*Urgency to act*

| Urgency to act | Description |
|---|---|
| **Watching in brief** | The evidence in these areas should be kept under review, with continuous monitoring of risk levels, so that further action can be taken if necessary. |
| **Sustain current action** | Current or planned levels of activity are appropriate, but continued implementation of these policies or plans is needed to ensure that the risk continues to be managed in future. A monitoring and evaluation process should be in place to evaluate policy effectiveness, with a view to continuous improvement. |
| **Further investigation** | The available knowledge is insufficient to call for specific new action. Priority should be given to gathering additional evidence regarding the severity of the risk as well as policy readiness, e.g. through dedicated research, monitoring or policy evaluation. |
| **More action needed** | The severity of risk and the limited level of policy readiness calls for more action to be implemented. It is crucial to initiate processes that strengthen adaptation action to avoid critical impacts of climate change. |
| **Urgent action needed** | The combination of catastrophic risks and insufficient policy readiness calls for urgent new, stronger or different action in the coming years to reduce climate risks. Such actions include policymaking, implementation, capacity building or enabling the environment for adaptation, over and above those already planned. |

# Annex 2

*List of input documents.*

| n. | Documents |
|---|---|
| 1 | Anzidei, M., et al. (2020). Deliverable D2.3 Sea level rise projections. SAVEMEDCOASTS-2 project. |
| 2 | Allegri, E., Zanetti, M., Torresan, S., & Critto, A. (2024). Pluvial flood risk assessment for 2021–2050 under climate change scenarios in the Metropolitan City of Venice. Science of the Total Environment, 914(March), 169925. https://doi.org/https://doi.org/10.1016/j.scitotenv.2024.169925. |
| 3 | Anzidei, M., Alberti, T., Vecchio, A., Loizidou, X., Orthodoxou, D., Serpelloni, E., Falciano, A., & Ferrari, C. (2024). Sea level rise and extreme events along the Mediterranean coasts: the case of Venice and the awareness of local population, stakeholders and policy makers. Rendiconti Lincei. Scienze Fisiche e Naturali, 35, 359–370. https://doi.org/https://doi.org/10.1007/s12210-024-01236-x. |
| 4 | ARPAV (2023). Deliverable D5.4.5 Multi-risk assessment in the Veneto Region pilot area: comparative analysis and prioritization of main impacts, vulnerabilities and risks related to climate change. Interreg Italy-Croatia AdriaClim project. |
| 5 | Barbi, A., Monai, M., Racca, R., & Rossa, A. M. (2012). Recurring features of extreme autumnall rainfall events on the Veneto coastal area. Natural Hazards & Earth System Sciences, 12(8), 2463–2477. https://doi.org/https://doi.org/10.5194/nhess-12-2463-2012. |
| 6 | Bonato, M., Sambo, B., Sperotto, A., Lambert, J. H., Linkov, I., Critto, A., Torresan, S., & Marcomini, A. (2021). Prioritization of Resilience Initiatives for Climate-Related Disasters in the Metropolitan City of Venice. Risk Analysis, 42(5), 931–952. https://doi.org/https://doi.org/10.1111/risa.13823. |
| 7 | Cavaleri, L., Bajo, M., Barbariol, F., Bastianini, M., Benetazzo, A., Bertotti, L., Chiggiato, J., Ferrarin, C., Trincardi, F., & Umgiesser, G. (2020). The 2019 Flooding of Venice AND ITS IMPLICATIONS FOR FUTURE PREDICTIONS. Oceanography, 33(1), 42–49. https://doi.org/https://www.jstor.org/stable/26897834. |
| 8 | Cavalieri, C. (2020). Extreme-city-territories. Coastal geographies in the Veneto region. Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 1–19. |
| 9 | Critto, A., Aslan, S., Allegri, E., Dal Barco, M.K., Fogarin, S., Furlan, E., Pham, V.H., Sperotto, A., Torresan, S., Zanetti, M., Zennaro, F. (2021). Deliverable D5.2.2.1 Analisi del rischio nello scenario baseline. Venezia2021 project. |
| 10 | Dal Barco, M. K., Maraschini, M., Ferrario, D. M., Nguyen, N. D., Torresan, S., Vascon, S., & Critto, A. (2024). A machine learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy). International Journal of Disaster Risk Reduction, 108(May), 104526. https://doi.org/10.1016/j.ijdrr.2024.104526. |
| 11 | Dal Barco, M. K., Maraschini, M., Nguyen, N. D., Ferrario, D. M., Rufo, O., Fonseca, H. L., Vascon, S., Torresan, S., & Critto, A. (n.d.). Integrating AI and Climate Change scenarios for multi-risk assessment in the coastal municipalities of the Veneto region. Science of the Total Environment, submitted. |
| 12 | EUCRA. (2024). European Climate Risk Assessment. In The European Climate Risk Assessment (EUCRA). https://doi.org/10.2800/204249. |
| 13 | Essenfelder, A.H., Torresan, S., Pal, J.S., Mysiak, J., Standardi, G. (2022). Deliverable D5.2 Report on the socio-economic assessment. SAVEMEDCOASTS-2 project. |
| 14 | Falciano, A., Anzidei, M., Greco, M., Trivigno, M. L., Vecchio, A., Georgiadis, C., Patias, P., Crosetto, M., Navarro, J., Serpelloni, E., Tolomei, C., Martino, G., Mancino, G., Arbia, F., Bignami, C., & Doumaz, F. (2023). The SAVEMEDCOASTS-2 webGIS: The Online Platform for Relative Sea Level Rise and Storm Surge Scenarios up to 2100 for the Mediterranean Coasts. Journal of Marine Science and Engineering, 11(11), 2071. https://doi.org/https://doi.org/10.3390/jmse11112071. |
| 15 | Falciano, A., Mancino, G., Trivigno, M.L., and Greco, M. (2021). Deliverable D4.1 Report on combined flooding scenarios through the implementation of expeditive methodologies and modelling. SAVEMEDCOASTS-2 project. |
| 16 | Ferrarin, C., Lionello, P., Orlić, M., Raicich, F., & Salvadori, G. (2022). Venice as a paradigm of coastal flooding under multiple compound drivers. Scientific Reports, 12, 5754. https://doi.org/https://doi.org/10.1038/s41598-022-09652-5. |
| 17 | Fogarin, S., Zanetti, M., Dal Barco, M. K., Zennaro, F., Furlan, E., Torresan, S., Pham, H. V., & Critto, A. (2023). Combining remote sensing analysis with machine learning to evaluate short-term coastal evolution trend in the shoreline of Venice. Science of the Total Environment, 859(1), 160293. https://doi.org/https://doi.org/10.1016/j.scitotenv.2022.160293. |

| | |
|---|---|
| 18 | Fogarin, S., Torresan, S., Critto, A. (2021). WP3 report - Scoping assessment and prioritization. Interreg Italy-Croatia AdriaClim project. |
| 19 | Fogarin, S., Dal Barco, M.K., Torresan, S., Critto, A. (2021). Veneto Coastal Pilot: Adaptation/Mitigation/Intervention Plan. Interreg Italy-Croatia AdriaClim project. |
| 20 | Fogarin, S., Dal Barco, M.K., Ferrario, D.M., Maraschini, M., Nguyean, N.D., Torresan, S., Critto, A. (2021). Assessment of vulnerability, hazards and impacts on the Pilot Areas. Interreg Italy-Croatia AdriaClim project. |
| 21 | Fontolan, G., Bezzi, A., Martinucci, D., Pillon, S., & Popesso, C. (2014). GCV - Geodatabase gestionale delle coste venete. |
| 22 | Fontolan, G., Pillon, S., Quadri, F. D., & Bezzi, A. (2007). Sediment storage at tidal inlets in northern Adriatic lagoons : Ebb-tidal delta morphodynamics , conservation and sand use strategies. 75, 261–277. https://doi.org/10.1016/j.ecss.2007.02.029. |
| 23 | Gallina, V., Torresan, S., Zabeo, A., Critto, A., Glade, T., & Marcomini, A. (2020). A multi-risk methodology for the assessment of climate change impacts in coastal zones. Sustainability (Switzerland). https://doi.org/10.3390/su12093697. |
| 24 | Gallina, V., Torresan, S., Zabeo, A., Rizzi, J., Carniel, S., Sclavo, M., Pizzol, L., Marcomini, A., & Critto, A. (2019). Assessment of climate change impacts in the North Adriatic coastal area. Part II: Consequences for coastal erosion impacts at the regional scale. Water (Switzerland), 11(6), 1–20. https://doi.org/10.3390/w11061300. |
| 25 | Greco, M., Arbia, F., Giampietro, R., Gruosso, P., Santangelo, E., Falciano, A., Mancino, G., Trivigno, M.L. (2021). Deliverable D4.2 - Report and maps on preliminary cascading effects due to combined flooding scenarios. SAVEMEDCOASTS-2 project. |
| 26 | Intergovernmental Panel on Climate Change, Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., Barrett, K., Blanco, G., Cheung, W. W. L., Connors, S. L., Denton, F., Diongue-Niang, A., Dodman, D., Garschagen, M., Geden, O., … Zommers, Z. (2023). Synthesis report of the IPCC Sixth Assessment Report (AR6) - Longer report. https://report.ipcc.ch/ar6syr/pdf/IPCC_AR6_SYR_LongerReport.pdf |
| 27 | Legambiente. (2012). Il consumo delle aree costiere italiane. La COSTA VENETA, da Bibione a Porto Tolle: l'aggressione del cemento e i cambiamenti del paesaggio. |
| 28 | Lionello, P., Barriopedro, D., Ferrarin, C., Nicholls, R. J., Orlic, M., Reale, M., Umgiesser, G., Vousdoukas, M., & Zanchettin, D. (2020). Extremes floods of Venice: characteristics, dynamics, past and future evolution. Natural Hazards and Earth System Sciences, November, 1–34. https://doi.org/https://doi.org/10.5194/nhess-2020-359. |
| 29 | Lionello, P., Galati, M. B., & Elvini, E. (2012). Extreme storm surge and wind wave climate scenario simulations at the Venetian littoral. Physics and Chemistry of the Earth, 40–41(Parts A/B/C), 86–92. https://doi.org/https://doi.org/10.1016/j.pce.2010.04.001. |
| 30 | Lionello, P., Nicholls, R. J., Umgiesser, G., & Zanchettin, D. (2021). Venice flooding and sea level: past evolution, present issues, and future projections (introduction to the special issue). Natural Hazards and Earth System Sciences, 21(8), 2633–2641. https://doi.org/10.5194/nhess-21-2633-2021. |
| 31 | Pham, H. V., Dal Barco, M. K., Cadau, M., Harris, R., Furlan, E., Torresan, S., Rubinetti, S., Zanchettin, D., Rubino, A., Kuznetsov, I., Barbariol, F., Benetazzo, A., Sclavo, M., & Critto, A. (2023). Multi-model chain for climate change scenario analysis to support coastal erosion and water quality risk management for the Metropolitan city of Venice. Science of the Total Environment, 904(June), 166310. https://doi.org/10.1016/j.scitotenv.2023.166310. |
| 32 | Pham, H. V., Dal Barco, M. K., Shahvar, M. P., Furlan, E., Critto, A., & Torresan, S. (2024). Bayesian Network Analysis for Shoreline Dynamics, Coastal Water Quality, and Their Related Risks in the Venice Littoral Zone, Italy. Journal of Marine Science and Engineering, 12(1), 139. https://doi.org/10.3390/jmse12010139. |
| 33 | Regione del Veneto - Direzione Ambiente e Transizione Ecologica. (2024). *SRACC \| Strategia Regionale di Adattamento ai Cambiamenti Climatici - Documento preliminare*. https://sharing.regione.veneto.it/index.php/s/ASCZEfgCLyigQQj. |
| 34 | Regione Veneto. (2024). Strategia Regionale di Adattamento ai Cambiamenti Climatici - RAPPORTO N.1: Clima e cambiamenti climatici in Veneto. https://sharing.regione.veneto.it/index.php/s/2aYbpawcn8H7jPn. |
| 35 | Regione Veneto. (2024). Strategia Regionale di Adattamento ai Cambiamenti Climatici - RAPPORTO N.2: Ricognizione degli strumenti di pianificazione regionale. https://sharing.regione.veneto.it/index.php/s/2aYbpawcn8H7jPn. |
| 36 | Regione Veneto. (2024). Strategia Regionale di Adattamento ai Cambiamenti Climatici - RAPPORTO N.3: Ricognizione degli strumenti di pianificazione comunale. https://sharing.regione.veneto.it/index.php/s/2aYbpawcn8H7jPn. |

| | |
|---|---|
| 37 | Regione Veneto. (2024). Strategia Regionale di Adattamento ai Cambiamenti Climatici - RAPPORTO N.4: Sviluppo di un indice di rischio climatico relativo alla scala regionale. https://sharing.regione.veneto.it/index.php/s/2aYbpawcn8H7jPn. |
| 38 | Regione Veneto. (2024). Strategia Regionale di Adattamento ai Cambiamenti Climatici - RAPPORTO N.5: Gli impatti socio-economici dei cambiamenti climatici in Veneto. https://sharing.regione.veneto.it/index.php/s/2aYbpawcn8H7jPn. |
| 39 | Sambo, B., Bonato, M., Sperotto, A., Torresan, S., Furlan, E., Lambert, J. H., Linkov, I., & Critto, A. (2023). Framework for multirisk climate scenarios across system receptors with application to the Metropolitan City of Venice. *Risk Analysis*, *43*(11), 2241–2261. https://doi.org/https://doi.org/10.1111/risa.14097. |
| 40 | Sambo, B., Sano, M., Sperotto, A., Zanetti, M., Torresan, S., Lambert, J. H., Linkov, I., & Critto, A. (2024). Sensitivity analysis for a participatory approach to enhance the climate resilience of Venice, Italy. Risk Analysis, 44(7), 1573–1585. https://doi.org/10.1111/risa.14258. |
| 41 | Serpelloni, E., Anzidei, M. (2020). Deliverable D2.1 Report on Land Subsidence from CGPS data. SAVEMEDCOASTS-2 project. |
| 42 | Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., Lawrence, J., Lempert, R. J., Muccione, V., Mackey, B., New, M. G., Neill, B. O., Reisinger, A., Roberts, D., Schmidt, D. N., & Seneviratne, S. (2021). A framework for complex climate change risk assessment. 489–501. https://doi.org/10.1016/j.oneear.2021.03.005. |
| 43 | Torresan, S., van Bakel, F., Boumpoulis, V., Harris, R., Essenfelder, A.H., Furlan, E., Fogarin, S., Critto, A. (2022) Deliverable D5.1 Report on the multi-hazard coastal risk index. SAVEMEDCOASTS-2 project. |
| 44 | Torresan, S., Critto, A., Rizzi, J., & Marcomini, A. (2012). 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 Science. https://doi.org/10.5194/nhess-12-2347-2012 |
| 45 | UNDRR. (2017). UNDRR: Terminology for Disaster Risk Reduction. https://www.undrr.org/terminology (last access: 13 April 2022) |
| 46 | Vousdoukas, M. I., Mentaschi, L., Voukouvalas, E., Verlaan, M., & Feyen, L. (2017). Extreme sea levels on the risealong Europe's coasts. Earth's Future, 5, 304–323. |
| 47 | Zanchettin, D., Bruni, S., Raicich, F., Lionello, P., Adloff, F., Androsov, A., Antonioli, F., Artale, V., Carminati, E., Ferrarin, C., Fofonova, V., Nicholls, R., Rubinetti, S., Rubino, A., Sannino, G., Spada, G., Thiéblemont, R., Tsimplis, M., Umgiesser, G., … Zerbini, S. (2020). Review article: Sea-level rise in Venice: historic and future trends. Natural Hazards and Earth System Sciences Discussions, November, 1–56. https://doi.org/10.5194/nhess-2020-351. |
| 48 | Zanetti, M., Allegri, E., Sperotto, A., Torresan, S., & Critto, A. (2022). Spatio-temporal cross-validation to predict pluvial flood events in the Metropolitan City of Venice. Journal of Hydrology, 612(B), 128150. https://doi.org/https://doi.org/10.1016/j.jhydrol.2022.128150. |
| 49 | Zennaro, F., Furlan, E., Simeoni, C., Torresan, S., Aslan, S., Critto, A., & Marcomini, A. (2021). Exploring machine learning potential for climate change risk assessment. Earth-Science Reviews, 220, 103752. https://doi.org/10.1016/J.EARSCIREV.2021.103752. |

# Annex 3

*Evaluation matrix collecting the responses of the local stakeholders and experts engaged to assess COAST-AId performance and its responses.*

| Prompt | Expert | Accuracy | Relevance | Clarity | Completeness | Conciseness |
|---|---|---|---|---|---|---|
| Prompt 1 | 1 | 5 - very high | 5 - very high | 4 - high | 5 - very high | 5 - very high |
| | 2 | 5 - very high | 5 - very high | 4 - high | 4 - high | 5 - very high |
| | 3 | 5 - very high | 5 - very high | 4 - high | 4 - high | 5 - very high |
| | 4 | 5 - very high | 5 - very high | 5 - very high | 4 - high | 5 - very high |
| | 5 | 4 - high | 5 - very high | 4 - high | 4 - high | 4 - high |
| | 6 | 5 - very high | 5 - very high | 4 - high | 4 - high | 5 - very high |
| Prompt 2 | 1 | 4 - high | 5 - very high | 4 - high | 5 - very high | 5 - very high |
| | 2 | 5 - very high | 5 - very high | 4 - high | 4 - high | 5 - very high |
| | 3 | 5 - very high | 5 - very high | 4 - high | 4 - high | 5 - very high |
| | 4 | 5 - very high | 3 - neutral | 5 - very high | 3 - neutral | 5 - very high |
| | 5 | 4 - high | 5 - very high | 3 - neutral | 4 - high | 5 - very high |
| | 6 | 5 - very high | 5 - very high | 4 - high | 5 - very high | 5 - very high |
| Prompt 3 | 1 | 4 - high | 5 - very high | 5 - very high | 5 - very high | 5 - very high |
| | 2 | 5 - very high | 5 - very high | 4 - high | 5 - very high | 4 - high |
| | 3 | 5 - very high | 5 - very high | 4 - high | 4 - high | 4 - high |
| | 4 | 5 - very high | 3 - neutral | 4 - high | 3 - neutral | 5 - very high |
| | 5 | 4 - high | 5 - very high | 3 - neutral | 2 - low | 5 - very high |
| | 6 | 5 - very high | 5 - very high | 5 - very high | 4 - high | 5 - very high |
| Prompt 4 | 1 | 4 - high | 5 - very high | 5 - very high | 5 - very high | 5 - very high |
| | 2 | 4 - high | 5 - very high | 4 - high | 3 - neutral | 5 - very high |
| | 3 | 5 - very high | 5 - very high | 3 - neutral | 4 - high | 5 - very high |
| | 4 | 5 - very high | 5 - very high | 5 - very high | 5 - very high | 5 - very high |
| | 5 | 5 - very high | 5 - very high | 5 - very high | 5 - very high | 3 - neutral |
| | 6 | 5 - very high | 5 - very high | 5 - very high | 5 - very high | 5 - very high |
| Prompt 5 | 1 | 4 - high | 5 - very high | 5 - very high | 5 - very high | 5 - very high |
| | 2 | 5 - very high | 5 - very high | 4 - high | 4 - high | 5 - very high |
| | 3 | 5 - very high | 5 - very high | 4 - high | 4 - high | 4 - high |
| | 4 | 5 - very high | 5 - very high | 5 - very high | 5 - very high | 5 - very high |
| | 5 | 4 - high | 5 - very high | 2 - low | 2 - low | 5 - very high |
| | 6 | 5 - very high | 5 - very high | 5 - very high | 5 - very high | 5 - very high |
| Prompt 6 | 1 | 5 - very high | 5 - very high | 4 - high | 4 - high | 5 - very high |
| | 2 | 4 - high | 4 - high | 4 - high | 3 - neutral | 4 - high |
| | 3 | 5 - very high | 5 - very high | 3 - neutral | 3 - neutral | 4 - high |
| | 4 | 4 - high | 5 - very high | 5 - very high | 5 - very high | 5 - very high |
| | 5 | 5 - very high | 5 - very high | 3 - neutral | 3 - neutral | 5 - very high |
| | 6 | 5 - very high | N/A | 5 - very high | N/A | 5 - very high |
| Prompt 7 | 1 | 5 - very high | 5 - very high | 4 - high | 3 - neutral | 5 - very high |
| | 2 | 4 - high | 4 - high | 4 - high | 3 - neutral | 5 - very high |
| | 3 | 5 - very high | 5 - very high | 5 - very high | 4 - high | 5 - very high |
| | 4 | 5 - very high | 4 - high | 4 - high | 3 - neutral | 5 - very high |
| | 5 | 5 - very high | 5 - very high | 3 - neutral | N/A | 5 - very high |
| | 6 | 5 - very high | N/A | 5 - very high | N/A | 5 - very high |
| Prompt 8 | 1 | 5 - very high | 5 - very high | 4 - high | 3 - neutral | 5 - very high |
| | 2 | 4 - high | 5 - very high | 5 - very high | 5 - very high | 5 - very high |
| | 3 | 5 - very high | 4 - high | 4 - high | 3 - neutral | 4 - high |
| | 4 | 5 - very high | 3 - neutral | 5 - very high | 3 - neutral | 5 - very high |
| | 5 | 5 - very high | 5 - very high | 3 - neutral | 3 - neutral | 5 - very high |
| | 6 | 5 - very high | N/A | 5 - very high | N/A | 5 - very high |
| Prompt 9 | 1 | 5 - very high | 5 - very high | 5 - very high | 4 - high | 5 - very high |
| | 2 | 4 - high | 5 - very high | 5 - very high | 4 - high | 5 - very high |
| | 3 | 5 - very high | 5 - very high | 4 - high | 4 - high | 5 - very high |
| | 4 | 5 - very high | 4 - high | 5 - very high | 4 - high | 5 - very high |
| | 5 | 4 - high | 5 - very high | 3 - neutral | 3 - neutral | 5 - very high |
| | 6 | 5 - very high | N/A | 5 - very high | N/A | 5 - very high |

# Acknowledgements

Throughout my Ph.D. journey, I have been inspired by the saying "*You can't control the wind, but you can adjust your sail*". These words reflect the essence of this experience: it's not about what happens to you, but how you react. This philosophy aligns perfectly with the invaluable lessons imparted to me by my supervisor and co-supervisors, to whom I owe immense gratitude.

To Prof. Andrea Critto, thank you for encouraging me to keep moving forward, helping me find my way when I needed it most.

To Dr. Silvia Torresan, thank you for teaching me the meaning of loyalty and for consistently pushing me beyond my perceived limits. Your unwavering belief in my abilities has helped me grow into a more confident researcher and person. For that, I am forever grateful.

To Dr. Sebastiano Vascon, thank you for your guidance through the most intricate challenges, always offering kindness and encouragement, helping me navigate even the toughest complexities.

I extend my heartfelt thanks to the Ph.D. Board in Science and Management of Climate Change, particularly Prof. Enrica De Cian and Prof. Francesco Bosello, for their engagement, feedback, and patience. During these years, we did our best to create a welcoming and supportive environment, hoping that future generations can pursue their ambitions with equal dedication.

To my fellow Ph.D. colleagues, I am profoundly grateful for the countless days and nights we spent unravelling complex problems together, while also honing our cooking skills. Together, we leaned on one another, forging friendships that I will always treasure.

To each researcher at CMCC, especially to those involved in the Interreg Italy-Croatia AdriaClim and H2020 MYRIAD-EU projects, thank you for the support and for sharing countless memorable moments.

To Federica, Elena, and Angelica, my heartfelt gratitude for embracing every idea with unwavering enthusiasm and helping bring them to life. Our mutual trust was truly pivotal.

My research journey began on a warm summer day back in summer 2018, marking the start of an incredible adventure. This thesis represents the culmination of the encouragement and inspiration I have drawn from the incredible people around me. To each of you, thank you.

# References


Abd-Elaty, I., Straface, S., & Kuriqi, A. (2021). Sustainable saltwater intrusion management in coastal aquifers under climatic changes for humid and hyper-arid regions. *Ecological Engineering*, *171*, 106382. https://doi.org/10.1016/j.ecoleng.2021.106382

AghaKouchak, A., Chiang, F., Huning, L. S., Love, C. A., Mallakpour, I., Mazdiyasni, O., Moftakhari, H., Papalexiou, S. M., Ragno, E., & Sadegh, M. (2020). Climate Extremes and Compound Hazards in a Warming World. *Annual Review of Earth and Planetary Sciences*, *48*, 519–548. https://doi.org/https://doi.org/10.1146/annurev-earth-071719-055228

Allegri, E., Zanetti, M., Torresan, S., & Critto, A. (2024). Pluvial flood risk assessment for 2021–2050 under climate change scenarios in the Metropolitan City of Venice. *Science of the Total Environment*, *914*(March), 169925. https://doi.org/https://doi.org/10.1016/j.scitotenv.2024.169925

Almasre, M. (2024). Development and Evaluation of a Custom GPT for the Assessment of Students' Designs in a Typography Course. *Education Sciences*, *14*(2), 148. https://doi.org/10.3390/educsci14020148

Anderies, J. M., & Barreteau, O. (2019). Governance principles for robust and resilient coastal systems in the face of global change. *Regional Environmental Change*, *19*(7), 1831–1833. https://doi.org/10.1007/s10113-019-01542-3

Antonellini, M., Mollema, P., Giambastiani, B., Bishop, K., Caruso, L., Minchio, A., Pellegrini, L., Sabia, M., Ulazzi, E., & Gabbianelli, G. (2008). Salt water intrusion in the coastal aquifer of the southern Po Plain, Italy. *Hydrogeology Journal*, *16*(8), 1541–1556. https://doi.org/10.1007/s10040-008-0319-9

Antonioli, F., Anzidei, M., Amorosi, A., Lo Presti, V., Mastronuzzi, G., Deiana, G., De Falco, G., Fontana, A., Fontolan, G., Lisco, S., Marsico, A., Moretti, M., Orrù, P. E., Sannino, G. M., Serpelloni, E., & Vecchio, A. (2017). Sea-level rise and potential drowning of the Italian coastal plains: Flooding risk scenarios for 2100. *Quaternary Science Reviews*, *158*, 29–43. https://doi.org/10.1016/j.quascirev.2016.12.021

Anzidei, M., Alberti, T., Vecchio, A., Loizidou, X., Orthodoxou, D., Serpelloni, E., Falciano, A., & Ferrari, C. (2024). Sea level rise and extreme events along the Mediterranean coasts: the case of Venice and the awareness of local population, stakeholders and policy makers. *Rendiconti Lincei. Scienze Fisiche e Naturali*, *35*, 359–370. https://doi.org/https://doi.org/10.1007/s12210-024-01236-x

Aslan, S., Zennaro, F., Furlan, E., & Critto, A. (2022). Recurrent neural networks for water quality assessment in complex coastal lagoon environments: A case study on the Venice Lagoon. *Environmental Modelling & Software*, *154*, 105403. https://doi.org/10.1016/j.envsoft.2022.105403

Baldi, P. (2012). Autoencoders, Unsupervised Learning, and Deep Architectures. *Proceedings of Machine Learning Research*, *27*, 37–49. https://proceedings.mlr.press/v27/baldi12a.html

Barbi, A., Cagnati, A., Cola, G., Checchetto, F., Chiaudani, A., Crepaz, A., Delillo, I., L, M., G, M., P, M., & SG, P. (2013). *Atlante climatico del Veneto. Precipitazioni-Basi informative per l'analisi delle correlazioni tra cambiamenti climatici e dinamiche forestali nel Veneto.*

Barbi, A., Monai, M., Racca, R., & Rossa, A. M. (2012). Recurring features of extreme autumnall rainfall events on the Veneto coastal area. *Natural Hazards & Earth System Sciences*, *12*(8), 2463–2477. https://doi.org/https://doi.org/10.5194/nhess-12-2463-2012

Bellafiore, D., Ferrarin, C., Maicu, F., Manfè, G., Lorenzetti, G., Umgiesser, G., Zaggia, L., & Levinson, A. V. (2021). Saltwater Intrusion in a Mediterranean Delta Under a Changing Climate. *Journal of Geophysical Research: Oceans*, *126*(2). https://doi.org/10.1029/2020JC016437

Bellizia, E., Boaga, J., Mozzi, P., Cassiani, G., D'Alpaos, A., Finotello, A., & Ghinassi, M. (2023). Impact of morpho-sedimentary heterogeneities on the evolution of coastal meandering rivers (Brenta River, Italy). *Geomorphology*, *437*, 108797. https://doi.org/10.1016/j.geomorph.2023.108797

Beretta, G. Pietro, & Terrenghi, J. (2017). Groundwater flow in the Venice lagoon and remediation of the Porto Marghera industrial area (Italy). *Hydrogeology Journal*, *25*(3), 847–861. https://doi.org/10.1007/s10040-016-

1517-5

Bezzi, A., Pillon, S., Martinucci, D., & Fontolan, G. (2018). Inventory and conservation assessment for the management of coastal dunes, Veneto coasts, Italy. *Journal of Coastal Conservation*, *22*, 503–518. https://doi.org/https://doi.org/10.1007/s11852-017-0580-y

Biolchi, S., Denamiel, C., Devoto, S., Korbar, T., Macovaz, V., Scicchitano, G., Vilibić, I., & Furlani, S. (2019). Impact of the October 2018 Storm Vaia on Coastal Boulders in the Northern Adriatic Sea. *Water*, *11*(11), 2229. https://doi.org/https://doi.org/10.3390/w11112229

Bolle, A., das Neves, L., Smets, S., Mollaert, J., & Buitrago, S. (2018). An impact-oriented Early Warning and Bayesian-based Decision Support System for flood risks in Zeebrugge harbour. *Coastal Engineering*, *134*(October 2017), 191–202. https://doi.org/10.1016/j.coastaleng.2017.10.006

Bonaldo, D., Bellafiore, D., Ferrarin, C., Ferretti, R., Ricchi, A., Sangelantoni, L., & Vitelletti, M. L. (2023). The summer 2022 drought: a taste of future climate for the Po valley (Italy)? *Regional Environmental Change*, *23*(1), 1. https://doi.org/10.1007/s10113-022-02004-z

Boudreault, J., Campagna, C., & Chebana, F. (2023). Machine and deep learning for modelling heat-health relationships. *Science of the Total Environment*, *892*, 164660. https://doi.org/https://doi.org/10.1016/j.scitotenv.2023.164660

Breiman, L. E. O. (2001). *Random Forests*. 5–32.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., … Amodei, D. (2020). Language Models are Few-Shot Learners. *Computer Science - Computation and Language*. https://doi.org/https://doi.org/10.48550/arXiv.2005.14165

Buchanan, M. K., Kopp, R. E., Oppenheimer, M., & Tebaldi, C. (2016). Allowances for evolving coastal flood risk under uncertain local sea-level rise. *Climatic Change*, *137*, 347–362. https://doi.org/https://doi.org/10.1007/s10584-016-1664-7

Buchanan, M. K., Oppenheimer, M., & Kopp, R. E. (2017). Amplification of flood frequencies with local sea level rise and emerging flood regimes. *Environmental Research Letters*, *12*(6), 064009. https://doi.org/10.1088/1748-9326/aa6cb3

Cahyana, N., Khomsah, S., & Aribowo, A. S. (2019). Improving Imbalanced Dataset Classification Using Oversampling and Gradient Boosting. *2019 5th International Conference on Science in Information Technology: Embracing Industry 4.0: Towards Innovation in Cyber Physical System, ICSITech 2019*, 217–222. https://doi.org/https://doi.org/10.1109/ICSITECH46713.2019.8987499

Camuffo, D. (2021). Four centuries of documentary sources concerning the sea level rise in Venice. *Climatic Change*, *167*(3–4), 1–16. https://doi.org/https://doi.org/10.1007/s10584-021-03196-9

Carbognin, L., Teatini, P., Tosi, L., Strozzi, T., & Tomasin, A. (2010). Present Relative Sea Level Rise in the Northern Adriatic Coastal Area. *Marine Research at CNR*, 1–10.

Castruccio, S., & Genton, M. G. (2018). Principles for statistical inference on big spatio-temporal data from climate models. *Statistics & Probability Letters*, *136*, 92–96. https://doi.org/10.1016/J.SPL.2018.02.026

Cavaleri, L., Bajo, M., Barbariol, F., Bastianini, M., Benetazzo, A., Bertotti, L., Chiggiato, J., Ferrarin, C., Trincardi, F., & Umgiesser, G. (2020). The 2019 Flooding of Venice AND ITS IMPLICATIONS FOR FUTURE PREDICTIONS. *Oceanography*, *33*(1), 42–49. https://doi.org/https://www.jstor.org/stable/26897834

Cavalieri, C. (2020). Extreme-city-territories. Coastal geographies in the Veneto region. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, 1–19.

Chang, C.-C., & Lin, C.-J. (2001). Training v-Support Vector Classifiers: Theory and Algorithms. *Neural Computation*, *13*(9), 2119–2147. https://doi.org/10.1162/089976601750399335

Chang, Y., Wang, X., Wang, J., Wu, Y., Yang, L., Zhu, K., Chen, H., Yi, X., Wang, C., Wang, Y., Ye, W., Zhang, Y., Chang, Y., Yu, P. S., Yang, Q., & Xie, X. (2024). A Survey on Evaluation of Large Language Models. *ACM Transactions on Intelligent Systems and Technology*, *15*(3), 1–45. https://doi.org/10.1145/3641289

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W.

P. (2002). SMOTE: Synthetic Minority Over-sampling Technique. *Journal Of Artificial Intelligence Research*, *16*, 321–357. https://doi.org/https://doi.org/10.1613/jair.953

Chen, R. C., Dewi, C., Huang, S. W., & Caraka, R. E. (2020). Selecting critical features for data classification based on machine learning methods. *Journal of Big Data*, *7*(1). https://doi.org/https://doi.org/10.1186/s40537-020-00327-4

Cheung, D. (2024). *An Introduction to LLM Evaluation: How to measure the quality of LLMs, prompts, and outputs*. Codesmith. https://www.codesmith.io/blog/an-introduction-to-llm-evaluation-how-to-measure-the-quality-of-llms-prompts-and-outputs

Claassen, J. N., Ward, P. J., Daniell, J., Koks, E. E., Tiggeloven, T., & Ruiter, M. C. (2023). A new method to compile global multi-hazard event sets. *Scientific Reports*, *13*, 13808. https://doi.org/https://doi.org/10.1038/s41598-023-40400-5

Coffinet, J., & Kien, J. N. (2019). Detection of rare events: A machine learning toolkit with an application to banking crises. *The Journal of Finance and Data Science*, *5*(4), 183–207. https://doi.org/https://doi.org/10.1016/J.JFDS.2020.04.001

Crespi, A., Terzi, S., Cocuccioni, S., Zebisch, M., Julie, B., & Füssel, H.-M. (2020). Climate-related hazard indices for Europe. *European Topic Centre on Climate Change Impacts, Vulnerability and Adaptation (ETC/CCA)*. https://doi.org/10.25424/cmcc/climate_related_hazard_indices_europe_2020

Cuccia, T., Guccio, C., & Rizzo, I. (2016). The effects of UNESCO World Heritage List inscription on tourism destinations performance in Italian regions. *Economic Modelling*, *53*, 494–508. https://doi.org/https://doi.org/10.1016/j.econmod.2015.10.049

Da Lio, C., Carol, E., Kruse, E., Teatini, P., & Tosi, L. (2015). Saltwater contamination in the managed low-lying farmland of the Venice coast, Italy: An assessment of vulnerability. *Science of The Total Environment*, *533*, 356–369. https://doi.org/10.1016/j.scitotenv.2015.07.013

Dal Barco, M. K., Furlan, E., Pham, H. V., Torresan, S., Zachopoulos, K., Kokkos, N., Sylaios, G., & Critto, A. (2024). Multi-scenario analysis in the Apulia shoreline: A multi-tiers analytical framework for the combined evaluation and management of coastal erosion and water quality risks. *Environmental Science & Policy*, *153*, 103665. https://doi.org/10.1016/j.envsci.2023.103665

Dal Barco, M. K., Maraschini, M., Ferrario, D. M., Nguyen, N. D., Torresan, S., Vascon, S., & Critto, A. (2024). A machine learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy). *International Journal of Disaster Risk Reduction*, *108*(15 June 2024), 104526. https://doi.org/10.1016/j.ijdrr.2024.104526

Dal Barco, M. K., Maraschini, M., Nguyen, N. D., Ferrario, D. M., Rufo, O., Fonseca, H. L., Vascon, S., Torresan, S., & Critto, A. (2025). Integrating AI and climate change scenarios for multi-risk assessment in the coastal municipalities of the Veneto region. *Science of The Total Environment*, *965*(15 February 2025), 178586. https://doi.org/10.1016/j.scitotenv.2025.178586

De Angeli, S., Malamud, B. D., Rossi, L., Taylor, F. E., Trasforini, E., & Rudari, R. (2022). A multi-hazard framework for spatial-temporal impact analysis. *International Journal of Disaster Risk Reduction*, *73*(15 April 2022), 102829. https://doi.org/https://doi.org/10.1016/j.ijdrr.2022.102829

de Coste, M., Li, Z., & Dibike, Y. (2022). Machine-learning approach for predicting the occurrence and timing of mid-winter ice breakups on canadian rivers. *Environmental Modelling and Software*, *152*. https://doi.org/https://doi.org/10.1016/j.envsoft.2022.105402

Del Vecchio, S., Sharma, S. K., Pavan, M., Acosta, A. T. R., Bacchetta, G., de Bello, F., Isermann, M., Michalet, R., & Buffa, G. (2022). Within-species variation of seed traits of dune engineering species across a European climatic gradient. *Frontiers in Plant Science*, *13*. https://doi.org/10.3389/fpls.2022.978205

Diaz, J. H., Brisolara, K. F., Harrington, D. J., Hu, C., & Katner, A. L. (2020). The Environmental Health Impact of Hurricane Katrina on New Orleans. *American Journal of Public Health*, *110*(10), 1480–1484. https://doi.org/10.2105/AJPH.2020.305809

Dogan, A., & Birant, D. (2021). Machine learning and data mining in manufacturing. *Expert Systems with Applications*, *166*, 114060. https://doi.org/https://doi.org/10.1016/J.ESWA.2020.11

4060

EC. (2010). *Towards a stronger European disaster response: the role of civil protection and humanitarian assistance*. https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2010:0600:FIN:EN:PDF

EC. (2019). Reporting Guidelines on Disaster Risk Management, Art. 6(1)d of Decision No 1313/2013/EU (2019/C 428/07). In *Official Journal of the European Union* (Issue C428). https://doi.org/10.31826/9781463235543-toc

EEA. (2018). National climate change vulnerability and risk assessments in Europe, 2018. In *European Environment Agency*.

Ertekin, S., Huang, J., & Giles, C. L. (2007). Active learning for class imbalance problem. *Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR'07*, 823–824. https://doi.org/https://doi.org/10.1145/1277741.1277927

EUCRA. (2024). European Climate Risk Assessment. In *The European Climate Risk Assessment (EUCRA)*. https://doi.org/10.2800/204249

Falciano, A., Anzidei, M., Greco, M., Trivigno, M. L., Vecchio, A., Georgiadis, C., Patias, P., Crosetto, M., Navarro, J., Serpelloni, E., Tolomei, C., Martino, G., Mancino, G., Arbia, F., Bignami, C., & Doumaz, F. (2023). The SAVEMEDCOASTS-2 webGIS: The Online Platform for Relative Sea Level Rise and Storm Surge Scenarios up to 2100 for the Mediterranean Coasts. *Journal of Marine Science and Engineering*, *11*(11), 2071. https://doi.org/https://doi.org/10.3390/jmse11112071

Faranda, D., Ginesta, M., Alberti, T., Coppola, E., & Anzidei, M. (2023). Attributing Venice Acqua Alta events to a changing climate and evaluating the efficacy of MoSE adaptation strategy. *Npj Climate and Atmospheric Science*, *6*(1), 181. https://doi.org/10.1038/s41612-023-00513-0

Fedele, G., Manco, I., Barbato, G., Verri, G., & Mercogliano, P. (2024). Evaluation of atmospheric indicators in the Adriatic coastal areas: a multi-hazards approach for a better awareness of the current and future climate. *Frontiers in Climate*, *6*(Coastal Climate Monitoring and Downscaling for Adaptation Planning in the Adriatic Sea), 1330299. https://doi.org/https://doi.org/10.3389/fclim.2024.1330299

Ferrarin, C., Lionello, P., Orlić, M., Raicich, F., & Salvadori, G. (2022). Venice as a paradigm of coastal flooding under multiple compound drivers. *Scientific Reports*, *12*, 5754. https://doi.org/https://doi.org/10.1038/s41598-022-09652-5

Ferrarin, C., Roland, A., Bajo, M., Umgiesser, G., Cucco, A., Davolio, S., Buzzi, A., Malguzzi, P., & Drofa, O. (2013). Tide-surge-wave modelling and forecasting in the Mediterranean Sea with focus on the Italian coast. *Ocean Modelling*, *61*, 38–48. https://doi.org/https://doi.org/10.1016/j.ocemod.2012.10.003

Ferrarin, C., Valentini, A., Vodopivec, M., Klaric, D., Massaro, G., Bajo, M., & Carraro, E. (2020). Integrated sea storm management strategy: the 29 October 2018 event in the Adriatic Sea. *Natural Hazards and Earth System Sciences*, *20*(1), 73–93.

Ferreira, Ó., Plomaritis, T. A., & Costas, S. (2019). Effectiveness assessment of risk reduction measures at coastal areas using a decision support system: Findings from Emma storm. *Science of the Total Environment*, *657*, 124–135. https://doi.org/10.1016/j.scitotenv.2018.11.478

Fogarin, S., Zanetti, M., Barco, M. K. D., Zennaro, F., Furlan, E., Torresan, S., Pham, H. V, & Critto, A. (2023). Combining remote sensing analysis with machine learning to evaluate short-term coastal evolution trend in the shoreline of Venice. *Science of the Total Environment*, *859*(November 2022), 160293. https://doi.org/10.1016/j.scitotenv.2022.160293

Fogarin, S., Zanetti, M., Dal Barco, M. K., Zennaro, F., Furlan, E., Torresan, S., Pham, H. V., & Critto, A. (2023). Combining remote sensing analysis with machine learning to evaluate short-term coastal evolution trend in the shoreline of Venice. *Science of the Total Environment*, *859*(1), 160293. https://doi.org/https://doi.org/10.1016/j.scitotenv.2022.160293

Fontolan, G., Bezzi, A., Martinucci, D., Pillon, S., & Popesso, C. (2014). *GCV - Geodatabase gestionale delle coste venete*.

Fontolan, G., Pillon, S., Quadri, F. D., & Bezzi, A. (2007). *Sediment storage at tidal inlets in northern Adriatic lagoons : Ebb-tidal delta morphodynamics ,*

*conservation and sand use strategies*. *75*, 261–277. https://doi.org/10.1016/j.ecss.2007.02.029

Fox-Kemper, B., H. T. Hewitt, C. Xiao, G. Aðalgeirsdóttir, S. S. Drijfhout, T. L. Edwards, N. R. Golledge, M. Hemer, R. E. Kopp, G. Krinner, A. Mix, D. Notz, S. Nowicki, I. S. Nurhati, L. Ruiz, J-B. Sallée, A. B. A. Slangen, Y. Y. (2021). *IPCC, 2021: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*.

Franceschini, R., Rosi, A., del Soldato, M., Catani, F., & Casagli, N. (2022). Integrating multiple information sources for landslide hazard assessment: the case of Italy. *Scientific Reports*, *12*(1), 20724. https://doi.org/10.1038/s41598-022-23577-z

Gallina, V., Torresan, S., Zabeo, A., Critto, A., Glade, T., & Marcomini, A. (2020). A multi-risk methodology for the assessment of climate change impacts in coastal zones. *Sustainability (Switzerland)*. https://doi.org/10.3390/su12093697

Gallina, V., Torresan, S., Zabeo, A., Rizzi, J., Carniel, S., Sclavo, M., Pizzol, L., Marcomini, A., & Critto, A. (2019). Assessment of climate change impacts in the North Adriatic coastal area. Part II: Consequences for coastal erosion impacts at the regional scale. *Water (Switzerland)*, *11*(6), 1–20. https://doi.org/10.3390/w11061300

Garner, G. G., Hermans, T., Kopp, R. E., Slangen, A. B. A., Edwards, T. L., Levermann, A., Nowikci, S., Palmer, M. D., Smith, C. B., Fox-Kemper, H. T., Hewitt, C., Xiao, G., Aðalgeirsdóttir, S. S. D., Edwards, T. L., Golledge, N. R., Hemer, M., Kopp, R. E., K, G., P., T., & P., B. (2021). *IPCC AR6 Sea-Level Rise Projections*.

Garner, G. G., Kopp, R. E., Hermans, T., Slangen, A. B. A., Koubbe, G., Turilli, M., Jha, S., Edwards, T. L., Levermann, A., Nowikci, S., Palmer, M. D., & Smith, C. (2023). The Framework for Assessing Changes To Sea-level (FACTS) v1.0-rc: A platform for characterizing parametric and structural uncertainty in future global, relative, and extreme sea-level change. *EGUsphere [Preprint]*. https://doi.org/https://egusphere.copernicus.org/preprints/2023/egusphere-2023-14/

Garrido-Merchán, E. C., Arroyo-Barrigüete, J. L., Borrás-Pala, F., Escobar-Torres, L., de Ibarreta, C. M., Ortiz-Lozano, J. M., & Rua-Vieites, A. (2023). *Real Customization or Just Marketing: Are Customized Versions of Chat GPT Useful?* http://arxiv.org/abs/2312.03728

Giannini, V., Bellucci, A., & Torresan, S. (2016). Sharing skills and needs between providers and users of climate information to create climate services: lessons from the Northern Adriatic case study. *Earth Perspectives*, *3*(1), 1. https://doi.org/10.1186/s40322-016-0033-z

Giorgi, F. (2019). Thirty Years of Regional Climate Modeling: Where Are We and Where Are We Going next? *Journal of Geophysical Research:Atmospheres*, *124*, 5696–5723. https://doi.org/https://doi.org/10.1029/2018JD030094

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Feedforward Networks*. https://mnassar.github.io/deeplearninghandbook/slides/06_mlp.pdf

Goswami, B. N., Venugopal, V., Sengupta, D., Madhusoodanan, M. S., & Xavier, P. K. (2006). Increasing Trend of Extreme Rain Events Over India in a Warming Environment. *Science*, *314*(5804), 1442–1445. https://doi.org/10.1126/science.1132027

Gualdi, S., Somot, S., May, W., Castellari, S., Déqué, M., Adani, M., Artale, V., Bellucci, A., Breitgand, J. S., Carillo, A., Cornes, R., Dell'Aquila, A., Dubois, C., Efthymiadis, D., Elizalde, A., Gimeno, L., Goodess, C. M., Harzallah, A., Krichak, S. O., … Xoplaki, E. (2013). Future Climate Projections. In *Regional Assessment of Climate Change in the Mediterranean* (vol 50, pp. 53–118). Springer, Dordrecht. https://doi.org/https://doi.org/10.1007/978-94-007-5781-3_3

Guo, Q., Mistry, M. N., Zhou, X., Zhao, G., Kino, K., Wen, B., Yoshimura, K., Satoh, Y., Cvijanovic, I., Kim, Y., Ng, C. F. S., Vicedo-Cabrera, A. M., Armstrong, B., Urban, A., Katsouyanni, K., Masselot, P., Tong, S., Sera, F., Huber, V., … Honda, Y. (2024). Regional variation in the role of humidity on city-level heat-related mortality. *PNAS Nexus*, *3*(8). https://doi.org/https://doi.org/10.1093/pnasnexus/pgae290

Hain, D. S., & Jurowetzki, R. (2020). Introduction to Rare-Event Predictive Modeling for Inferential Statisticians-A Hands-On Application in the Prediction of Breakthrough Patents. *Financial Econometrics: Bayesian Analysis, Quantum Uncertainty, and Related Topics*, *427*(ECONVN 2022. Studies in Systems, Decision and Control). https://doi.org/https://doi.org/10.1007/978-3-

030-98689-6_5

Halpern, B. S., Frazier, M., Afflerbach, J., Lowndes, J. S., Micheli, F., O'Hara, C., Scarborough, C., & Selkoe, K. A. (2019). Recent pace of change in human impact on the world's ocean. *Scientific Reports*, *9*(1), 1–8. https://doi.org/10.1038/s41598-019-47201-9

Hamon, R., Junklewitz, H., & Sanchez, I. (2020). *Robustness and Explainability of Artificial Intelligence - From technical to policy solutions*. https://doi.org/10.2760/57493

He, J., & Cheng, M. X. (2021). Weighting Methods for Rare Event Identification From Imbalanced Datasets. *Frontiers in Big Data*, *4*(108). https://doi.org/https://doi.org/10.3389/FDATA.2021.715320/XML/NLM

Hegelich, S. (2016). Decision Trees and Random Forests: Machine Learning Techniques to Classify Rare Events. *European Policy Analysis*, *2*(1), 98–120. https://doi.org/https://doi.org/10.18278/EPA.2.1.7

Hernández-Delgado, E. A. (2015). The emerging threats of climate change on tropical coastal ecosystem services, public health, local economies and livelihood sustainability of small islands: Cumulative impacts and synergies. *Marine Pollution Bulletin*, *101*(1), 5–28. https://doi.org/10.1016/j.marpolbul.2015.09.018

Hochrainer-Stigler, S., Trogrlić, R. Š., Reiter, K., Ward, P. J., de Ruiter, M. C., Duncan, M. J., Torresan, S., Ciurean, R., Mysiak, J., Stuparu, D., & Gottardo, S. (2023). Toward a framework for systemic multi-hazard and multi-risk assessment and management. *IScience*, *26*(5), 106736. https://doi.org/https://doi.org/10.1016/j.isci.2023.106736

Huntingford, C., Jeffers, E. S., Bonsall, M. B., Christensen, H. M., Lees, T., & Yang, H. (2019). Machine learning and artificial intelligence to aid climate change research and preparedness. *Environmental Research Letters*, *14*, 124007. https://doi.org/10.1088/1748-9326/ab4e55

Hurst, A., Lerer, A., Goucher, A. P., Perelman, A., Ramesh, A., Clark, A., Ostrow, A., Welihinda, A., Hayes, A., Radford, A., Mądry, A., Baker-Whitcomb, A., Beutel, A., Borzunov, A., Carney, A., Chow, A., Kirillov, A., Nichol, A., Paino, A., … Malkov, Y. (2024). *GPT-4o System Card*. http://arxiv.org/abs/2410.21276

Intergovernmental Panel on Climate Change, Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., Barrett, K., Blanco, G., Cheung, W. W. L., Connors, S. L., Denton, F., Diongue-Niang, A., Dodman, D., Garschagen, M., Geden, O., … Zommers, Z. (2023). *Synthesis report of the IPCC Sixth Assessment Report (AR6) - Longer report*. https://report.ipcc.ch/ar6syr/pdf/IPCC_AR6_SYR_LongerReport.pdf

IPBES. (2018). *Summary for policymakers of the regional assessment report on biodiversity and ecosystem services for Europe and Central Asia of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services.*

IPCC. (2018). IPCC Global Warming of 1.5°C Summary For Policymakers. In *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,.*

ISO/IEC 31010:2019 Risk Management – Risk Assessment Techniques (2019).

ISTAT. (2021). *Annuario Statistico Italiano 2021*. https://www.istat.it/storage/ASI/2021/ASI_2021.pdf

Jäger, W. S., Christie, E. K., Hanea, A. M., den Heijer, C., & Spencer, T. (2018). A Bayesian network approach for coastal risk analysis and decision making. *Coastal Engineering*, *134*(January), 48–61. https://doi.org/10.1016/j.coastaleng.2017.05.004

Janizadeh, S., Pal, S. C., Saha, A., Chowdhuri, I., Ahmadi, K., Mirzaei, S., Mosavi, A. H., & Tiefenbacher, J. P. (2021). Mapping the spatial and temporal variability of flood hazard affected by climate and land-use changes in the future. *Journal of Environmental Management*, *298*, 113551. https://doi.org/https://doi.org/10.1016/j.jenvman.2021.113551

Jelic, D., Telišman Prtenjak, M., Malecic, B., Belušic Vozila, A., Megyeri, O. A., & Renko, T. (2021). A New Approach for the Analysis of Deep Convective Events: Thunderstorm Intensity Index. *Atmosphere*, *12*(7), 908. https://doi.org/https://doi.org/10.3390/atmos12070908

Kalla, D., Smith, N., Kuraku, S., & Samaah, F. (2023). Study and Analysis of Chat GPT and its Impact on Different Fields of Study. *International Journal of Innovative Science and Research Technology*, *8*(3), 827–833.

https://ssrn.com/abstract=4402499

Kashinath, K., Mustafa, M., Albert, A., Wu, J.-L., Jiang, C., Esmaeilzadeh, S., Azizzadenesheli, K., Wang, R., Chattopadhyay, A., Singh, A., Manepalli, A., Chirila, D., Yu, R., Walters, R., White, B., Xiao, H., Tchelepi, H. A., Marcus, P., Anandkumar, A., … Prabhat. (2021). Physics-informed machine learning: case studies for weather and climate modelling. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *379*(2194), 20200093. https://doi.org/https://doi.org/10.1098/rsta.2020.0093

Khot, T., Trivedi, H., Finlayson, M., Fu, Y., Richardson, K., Clark, P., & Sabharwal, A. (2022). Decomposed Prompting: A Modular Approach for Solving Complex Tasks. *Computer Science - Computation and Language*. https://doi.org/https://doi.org/10.48550/arXiv.2210.02406

King, G., Langche Zeng, G. H. E., Alt, J., Freeman, J., Gleditsch, K., Imbens, G., Manski, C., Mccullagh, P., Mebane, W., Nagler, J., Russett, B., Scheve, K., Schrodt, P., Tanner, M., Tucker, R., Bennett, S., Huth, P., & Zeng, L. (2001). Logistic Regression in Rare Events Data. *Political Analysis*, *9*(2), 137–163. https://doi.org/https://doi.org/10.1093/OXFORDJOURNALS.PAN.A004868

Kojima, T., Gu, S. S., Reid, M., Matsuo, Y., & Iwasawa, Y. (2022). Large Language Models are Zero-Shot Reasoners. *Computer Science - Computation and Language*. https://doi.org/https://doi.org/10.48550/arXiv.2205.11916

Kroll, M., & Kraus, K. (2024). *Optimizing the role of human evaluation in LLM-based spoken document summarization systems*. https://doi.org/10.21437/Interspeech.2024-2268

L'Hévéder, B., Li, L., Sevault, F., & Somot, S. (2013). Interannual variability of deep convection in the Northwestern Mediterranean simulated with a coupled AORCM. *Climate Dynamics*, *41*(3), 937–960. https://doi.org/https://doi.org/10.1007/s00382-012-1527-5

Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Pritzel, A., S., R., Ewalds, T., Alet, F., Eaton-Rosen, Z., Hu, W., Merose, A., Hoyer, S., Holland, G., Stott, J., Vinyals, O., Mohamed, S., & Battaglia, P. (2022). *GraphCast: Learning skillful medium-range global weather forecasting*. https://doi.org/https://doi.org/10.48550/arXiv.2212.12794

Laurin, G. V., Francini, S., Luti, T., Chirici, G., Pirotti, F., & Papale, D. (2021). Satellite open data to monitor forest damage caused by extreme climate-induced events: a case study of the Vaia storm in Northern Italy. *Forestry: An International Journal of Forest Research*, *94*(3), 407–416. https://doi.org/https://doi.org/10.1093/forestry/cpaa043

Legambiente. (2012). *Il consumo delle aree costiere italiane. La COSTA VENETA, da Bibione a Porto Tolle: l'aggressione del cemento e i cambiamenti del paesaggio.*

Lionello, P., Barriopedro, D., Ferrarin, C., Nicholls, R. J., Orlic, M., Reale, M., Umgiesser, G., Vousdoukas, M., & Zanchettin, D. (2020). Extremes floods of Venice: characteristics, dynamics, past and future evolution. *Natural Hazards and Earth System Sciences*, *November*, 1–34. https://doi.org/https://doi.org/10.5194/nhess-2020-359

Lionello, P., Galati, M. B., & Elvini, E. (2012). Extreme storm surge and wind wave climate scenario simulations at the Venetian littoral. *Physics and Chemistry of the Earth*, *40–41*(Parts A/B/C), 86–92. https://doi.org/https://doi.org/10.1016/j.pce.2010.04.001

Lionello, P., Nicholls, R. J., Umgiesser, G., & Zanchettin, D. (2021). Venice flooding and sea level: past evolution, present issues, and future projections (introduction to the special issue). *Natural Hazards and Earth System Sciences*, *21*(8), 2633–2641. https://doi.org/10.5194/nhess-21-2633-2021

Liu, F. T., Ting, K. M., & Zhou, Z.-H. (2008). Isolation Forest. *Eighth IEEE International Conference on Data Mining*, 413–422. https://doi.org/https://doi.org/10.1109/ICDM.2008.17

Liu, Z., & Bondell, H. D. (2019). Binormal Precision–Recall Curves for Optimal Classification of Imbalanced Data. *Statistics in Biosciences*, *11*, 141–161. https://doi.org/https://doi.org/10.1007/s12561-019-09231-9

Lonsdale, J., Nicholson, R., Judd, A., Elliott, M., & Clarke, C. (2020). A novel approach for cumulative impacts assessment for marine spatial planning. *Environmental Science and Policy*, *106*(February), 125–135.

https://doi.org/10.1016/j.envsci.2020.01.011

Lovrinović, I., Bergamasco, A., Srzić, V., Cavallina, C., Holjević, D., Donnici, S., Erceg, J., Zaggia, L., & Tosi, L. (2021). Groundwater Monitoring Systems to Understand Sea Water Intrusion Dynamics in the Mediterranean: The Neretva Valley and the Southern Venice Coastal Aquifers Case Studies. *Water*, *13*(4), 561. https://doi.org/10.3390/w13040561

Luca, S., Karsmakers, P., Cuppens, K., Croonenborghs, T., van de Vel, A., Ceulemans, B., Lagae, L., van Huffel, S., & Vanrumste, B. (2014). Detecting rare events using extreme value statistics applied to epileptic convulsions in children. *Artificial Intelligence in Medicine*, *60*(2), 89–96. https://doi.org/https://doi.org/10.1016/J.ARTMED.2013.11.007

Luo, J., Straffelini, E., Bozzolan, M., Zheng, Z., & Tarolli, P. (2024). Saltwater intrusion in the Po River Delta (Italy) during drought conditions: Analyzing its spatio-temporal evolution and potential impact on agriculture. *International Soil and Water Conservation Research*, *12*(3), 714–725. https://doi.org/10.1016/j.iswcr.2023.09.009

Maalouf, M., & Trafalis, T. B. (2011). Robust weighted kernel logistic regression in imbalanced and rare events data. *Computational Statistics & Data Analysis*, *55*(1), 168–183. https://doi.org/https://doi.org/10.1016/J.CSDA.2010.06.014

Malik, N., & Ozturk, U. (2020). Rare events in complex systems: Understanding and prediction. *Chaos*, *30*, 90401. https://doi.org/https://doi.org/10.1063/5.0024145

Marcos, M., Rohmer, J., Vousdoukas, M. I., Mentaschi, L., Le Cozannet, G., & Amores, A. (2019). Increased extreme coastal water levels due to the combined action of storm surges and wind waves. *Geophysical Research Letters*, *46*, 4356–4364. https://doi.org/https://doi.org/10.1029/2019GL082599

Marsico, A., Lisco, S., Presti, V. Lo, Antonioli, F., Amorosi, A., Anzidei, M., Deiana, G., Falco, G. De, Fontana, A., Fontolan, G., Moretti, M., Orrú, P. E., Serpelloni, E., Sannino, G., Vecchio, A., Marsico, A., Lisco, S., Presti, V. Lo, Antonioli, F., … Serpelloni, E. (2017). *Flooding scenario for four Italian coastal plains using three relative sea level rise models*. *5647*. https://doi.org/10.1080/17445647.2017.1415989

MATTM. (2017). *Piano Nazionale di Adattamento ai Cambiamenti Climatici PNACC*.

Meena, S. R., Puliero, S., Bhuyan, K., Floris, M., & Catani, F. (2022). Assessing the importance of conditioning factor selection in landslide susceptibility for the province of Belluno (region of Veneto, northeastern Italy). *Natural Hazards and Earth System Sciences*, *22*(4), 1395–1417. https://doi.org/10.5194/nhess-22-1395-2022

Mel, R. A., Viero, D. P., Carniello, L., & D'Alpaos, L. (2020). Optimal floodgate operation for river flood management: The case study of Padova (Italy). *Journal of Hydrology: Regional Studies*, *30*, 100702. https://doi.org/10.1016/j.ejrh.2020.100702

Méndez-Tejeda, R., & Hernández-Ayala, J. J. (2023). Links between climate change and hurricanes in the North Atlantic. *PLOS Climate*, *2*(4), e0000186. https://doi.org/10.1371/journal.pclm.0000186

Menegatto, M., Freschi, G., Bulfon, M., & Zamperini, A. (2024). Collectively Remembering Environmental Disasters: The Vaia Storm as a Case Study. *Sustainability*, *16*(19), 8418. https://doi.org/10.3390/su16198418

Mentaschi, L., Vousdoukas, M. I., Pekel, J. F., Voukouvalas, E., & Feyen, L. (2018). Global long-term observations of coastal erosion and accretion. *Scientific Reports*, *8*(1), 1–11. https://doi.org/10.1038/s41598-018-30904-w

Moharana, S. S., & Swain, D. (2023). On the recent increase in Atlantic Ocean hurricane activity and influencing factors. *Natural Hazards*, *118*(2), 1387–1399. https://doi.org/10.1007/s11069-023-06061-3

Murtagh, F. (1991). Multilayer perceptrons for classification and regression. *Neurocomputing*, *2*(5–6), 183–197. https://doi.org/https://doi.org/10.1016/0925-2312(91)90023-5

Nazarnia, H., Nazarnia, M., Sarmasti, H., & Wills, W. O. (2020). A Systematic Review of Civil and Environmental Infrastructures for Coastal Adaptation to Sea Level Rise. *Civil Engineering Journal*, *6*(7), 1375–1399. https://doi.org/10.28991/cej-2020-03091555

Ng, A. (2021). *Machine Learning*. Cs229.Stanford.Edu; Stanford University. http://cs229.stanford.edu/

Nicholls, R. J., Wong, P. P., Burkett, V. R., Codignotto, J. O., Hay, J. E., McLean, R. F., Ragoonaden, S., & Woodroffe, C. D. (2007). Coastal systems and low-lying areas. In P. J. van der L. and , M.L. Parry, O.F. Canziani,

J.P. Palutikof & E. C.E. Hanson (Eds.), *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 315–356). Cambridge University Press, Cambridge, UK.

Nieves, V., Radin, C., & Camps-Valls, G. (2021). Predicting regional coastal sea level changes with machine learning. *Scientific Reports*, *11*, 7650. https://doi.org/https://doi.org/10.1038/s41598-021-87460-z

O'Leary, B. C., Wood, L. E., Cornet, C., Roberts, C. M., & Fonseca, C. (2024). Practitioner insights on challenges and options for advancing blue Nature-based Solutions. *Marine Policy*, *163*, 106104. https://doi.org/10.1016/j.marpol.2024.106104

OpenAI. (2023). *GPT-4 Technical Report* (pp. 1–100). https://cdn.openai.com/papers/gpt-4.pdf

Pantalona, G., Tsalakanidou, F., Nikolopoulos, S., Kompatsiaris, I., Lombardo, F., Norbiato, D., Ferri, M., Kovats, L., & Haberstock, H. (2021). Decision support system for flood risk reduction policies: The case of a flood protection measure in the area of Vicenza. *Data & Policy*, *3*, e26. https://doi.org/10.1017/dap.2021.23

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

Park, S. J., & Lee, D. K. (2020b). Prediction of coastal flooding risk under climate change impacts in South Korea using machine learning algorithms. *Environmental Research Letters*, *15*(9), 94052. https://doi.org/10.1088/1748-9326/aba5b3

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, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*(85), 2825–2830.

Pham, H. V., Dal Barco, M. K., Cadau, M., Harris, R., Furlan, E., Torresan, S., Rubinetti, S., Zanchettin, D., Rubino, A., Kuznetsov, I., Barbariol, F., Benetazzo, A., Sclavo, M., & Critto, A. (2023). Multi-model chain for climate change scenario analysis to support coastal erosion and water quality risk management for the Metropolitan city of Venice. *Science of the Total Environment*, *904*(June), 166310. https://doi.org/10.1016/j.scitotenv.2023.166310

Pham, H. V., Dal Barco, M. K., Shahvar, M. P., Furlan, E., Critto, A., & Torresan, S. (2024). Bayesian Network Analysis for Shoreline Dynamics, Coastal Water Quality, and Their Related Risks in the Venice Littoral Zone, Italy. *Journal of Marine Science and Engineering*, *12*(1), 139. https://doi.org/10.3390/jmse12010139

Plomaritis, T. A., Costas, S., & Ferreira, Ó. (2018). Use of a Bayesian Network for coastal hazards, impact and disaster risk reduction assessment at a coastal barrier (Ria Formosa, Portugal). *Coastal Engineering*, *134*(September), 134–147. https://doi.org/10.1016/j.coastaleng.2017.07.003

Poljansek, K., Casajus Valles, A., Marin Ferrer, M., De Jager, A., Dottori, F., Galbusera, L., Garcia Puerta, B., Giannopoulos, G., Girgin, S., Hernandez Ceballos, M., Iurlaro, G., Karlos, V., Krausmann, E., Larcher, M., Lequarre, A., Theocharidou, M., Montero Prieto, M., Naumann, G., Necci, A., … Wood, M. (2019). *Recommendations for National Risk Assessment for Disaster Risk Management in EU*. Publications Office of the European Union. https://doi.org/10.2760/147842

Raicich, F. (2018). *Studio conoscitivo dei cambiamenti climatici e di alcuni lori impatti in Friuli Venezia Giulia*. https://doi.org/https://www.meteo.fvg.it/clima/clima_fvg/03_cambiamenti_climatici/01_REPORT_cambiamenti_climatici_e_impatti_per_il_FVG/impattiCCinFVG_marzo2018.pdf

Raker, E. J., & Woods, T. (2023). Disastrous Burdens: Hurricane Katrina, Federal Housing Assistance, and Well-Being. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, *9*(5), 122–143. https://doi.org/10.7758/RSF.2023.9.5.06

Rana, M. S., & Mahanta, C. (2023). Spatial prediction of flash flood susceptible areas using novel ensemble of bivariate statistics and machine learning techniques for ungauged region. *Natural Hazards*, *115*, 947–969. https://doi.org/https://doi.org/10.1007/s11069-022-05580-9

Rao, V., Maulik, R., Constantinescu, E., & Anitescu, M. (2020). A machine-learning-based importance sampling method to compute rare event probabilities. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in*

*Bioinformatics)*, *12142 LNCS*, 169–182. https://doi.org/https://doi.org/10.1007/978-3-030-50433-5_14/FIGURES/

Rasmussen, D. J., Bittermann, K., Buchanan, M. K., Kulp, S., Strauss, B. H., Kopp, R. E., & Oppenheimer, M. (2018). Extreme sea level implications of 1.5 °C, 2.0 °C, and 2.5 °C temperature stabilization targets in the 21st and 22nd centuries. *Environmental Research Letters*, *13*(3), 034040. https://doi.org/10.1088/1748-9326/aaac87

Raveh-Rubin, S., & Wernli, H. (2015). Large-scale wind and precipitation extremes in the Mediterranean: aclimatological analysis for 1979–2012. *Quarterly Journal of the Royal Meteorological Society*, *141*(681), 2404–2417. https://doi.org/https://doi.org/10.1002/qj.2531

Regione del Veneto - Direzione Ambiente e Transizione Ecologica. (2024). *SRACC | Strategia Regionale di Adattamento ai Cambiamenti Climatici - Documento preliminare*. https://sharing.regione.veneto.it/index.php/s/ASCZEfgCLyigQQj

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & P. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195–204. https://doi.org/https://doi.org/10.1038/s41586-019-0912-1

Reimann, L., Vafeidis, A. T., Brown, S., Hinkel, J., & Tol, R. S. J. (2018). Mediterranean UNESCO World Heritage at risk from coastal flooding and erosion due to sea-level rise. *Nature Communications*, *9*(1). https://doi.org/10.1038/s41467-018-06645-9

Ruol, P., Martinelli, L., & Favaretto, C. (2018). Vulnerability analysis of the Venetian littoral and adopted mitigation strategy. *Water*, *10*(8), 984.

Ruol, P., Martinelli, L., Favaretto, C., Pinato, T., Galiazzo, F., Patti, S., Anti, U., Piazza, R., Simonin, P., & Selvi, G. (2016). *Gestione integrata della Zona costiera studio e monitoraggio per la definizione degli interventi di difesa dei litorali dall'erosione nella Regione Veneto-linee guida*.

Ruti, P. M., Somot, S., Giorgi, F., Dubois, C., Flaounas, E., Obermann, A., Dell'Aquila, A., Pisacane, G., Harzallah, A., Lombardi, E., Ahrens, B., Akhtar, N., Alias, A., Arsouze, T., Aznar, R., Bastin, S., Bartholy, J., Béranger, K., Beuvier, J., … Vervatis, V. (2016). Med-CORDEX Initiative for Mediterranean Climate Studies. *Bulletin of the American Meteorological Society*, *97*(7), 1187–1208. https://doi.org/https://doi.org/10.1175/BAMS-D-14-00176.1

Saha, A., Pal, S. C., Santosh, M., Janizadeh, S., Chowdhuri, I., Norouzi, A., Roy, P., & Chakrabortty, R. (2021). Modelling multi-hazard threats to cultural heritage sites and environmental sustainability: The present and future scenarios. *Journal of Cleaner Production*, *320*, 128713. https://doi.org/https://doi.org/10.1016/j.jclepro.2021.128713

Šakić Trogrlić, R., Reiter, K., Ciurean, R. L., Gottardo, S., Torresan, S., Daloz, A. S., Ma, L., Padrón Fumero, N., Tatman, S., Hochrainer-Stigler, S., de Ruiter, M. C., Schlumberger, J., Harris, R., Garcia-Gonzalez, S., García-Vaquero, M., Arévalo, T. L. F., Hernandez-Martin, R., Mendoza-Jimenez, J., Ferrario, D. M., … Ward, P. J. (2024). Challenges in assessing and managing multi-hazard risks: A European stakeholders perspective. *Environmental Science and Policy*, *157*(August 2023). https://doi.org/10.1016/j.envsci.2024.103774

Sambo, B., Bonato, M., Sperotto, A., Torresan, S., Furlan, E., Lambert, J. H., Linkov, I., & Critto, A. (2023). Framework for multirisk climate scenarios across system receptors with application to the Metropolitan City of Venice. *Risk Analysis*, *43*(11), 2241–2261. https://doi.org/https://doi.org/10.1111/risa.14097

Sampurno, J., Vallaeys, V., Ardianto, R., & Hanert, E. (2022). Integrated hydrodynamic and machine learning models for compound flooding prediction in a data-scarce estuarine delta. *Nonlinear Processes in Geophysics*, *29*, 301–315. https://doi.org/https://doi.org/10.5194/npg-29-301-2022

Sanuy, M., & Jiménez, J. A. (2021). Probabilistic characterisation of coastal storm-induced risks using Bayesian networks. *Natural Hazards and Earth System Sciences*, *21*(1), 219–238. https://doi.org/10.5194/nhess-21-219-2021

Sarhadi, A., Burn, D. H., Yang, G., & Ghodsi, A. (2017). Advances in projection of climate change impacts using supervised nonlinear dimensionality reduction techniques. *Climate Dynamics*, *48*, 1329–1351. https://doi.org/https://doi.org/10.1007/s00382-016-3145-0

Schickhoff, U., Bobrowski, M., Böhner, J., Bürzle, B.,

Chaudhary, R. P., Gerlitz, L., Lange, J., Müller, M., Scholten, T., & Schwab, N. (2016). Climate Change and Treeline Dynamics in the Himalaya. *Climate Change, Glacier Response, and Vegetation Dynamics in the Himalaya*. https://doi.org/https://doi.org/10.1007/978-3-319-28977-9_15

Schimanke, S., Ridal, M., Le Moigne, P., Berggren, L., Undén, P., Randriamampianina, R., Andrea, U., Bazile, E., Bertelsen, A., Brousseau, P., Dahlgren, P., Edvinsson, L., El Said, A., Glinton, M., Hopsch, S., Isaksson, L., Mladek, R., Olsson, E., Verrelle, A., & Wang, Z. Q. (2021). *CERRA sub-daily regional reanalysis data for Europe on single levels from 1984 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS)*. https://doi.org/10.24381/cds.622a565a

Schulhoff, S., Ilie, M., Balepur, N., Kahadze, K., Liu, A., Si, C., Li, Y., Gupta, A., Han, H., Schulhoff, S., Dulepet, P. S., Vidyadhara, S., Ki, D., Agrawal, S., Pham, C., Kroiz, G., Li, F., Tao, H., Srivastava, A., … Resnik, P. (2024). The Prompt Report: A Systematic Survey of Prompting Techniques. *Computer Science - Computation and Language*, *15 July 2024*. https://doi.org/https://doi.org/10.48550/arXiv.2406.06608

Scorzini, A. R., & Frank, E. (2015). Flood damage curves: new insights from the 2010 flood in Veneto, Italy. *Journal of Flood Risk Management*, *10*, 381–392. https://doi.org/10.1111/jfr3.12163

Shek-Noble, L. (2023). Communicating Vulnerability in Disasters: Media Coverage of People with Disabilities in Hurricane Katrina and the Tōhoku Earthquake and Tsunami. In *The Palgrave Handbook of Disability and Communication* (pp. 295–316). Springer International Publishing. https://doi.org/10.1007/978-3-031-14447-9_18

Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., Lawrence, J., Lempert, R. J., Muccione, V., Mackey, B., New, M. G., Neill, B. O., Reisinger, A., Roberts, D., Schmidt, D. N., & Seneviratne, S. (2021). *A framework for complex climate change risk assessment*. 489–501. https://doi.org/10.1016/j.oneear.2021.03.005

Singh, G. G., Hilmi, N., Bernhardt, J. R., Cisneros Montemayor, A. M., Cashion, M., Ota, Y., Acar, S., Brown, J. M., Cottrell, R., & Djoundourian, S. (2019). Climate impacts on the ocean are making the Sustainable Development Goals a moving target travelling away from us. *People and Nature*, *1*(3), 317–330.

Sorokin, L. V. (2018). The Experience of Disaster Risk Reduction and Economic Losses Reduction in Malaysia During the Water Crisis 1998 in the Context of the Next El Nino Strongest on Record Maximum 2015. In C. Mal, S., Singh, R., Huggel (Ed.), *Climate Change, Extreme Events and Disaster Risk Reduction*. https://doi.org/https://doi.org/10.1007/978-3-319-56469-2_16

Stocchi, P., & Davolio, S. (2017). Intense air-sea exchanges and heavy orographic precipitation over Italy: The role of Adriatic sea surface temperature uncertainty. *Atmospheric Research*, *196*, 62–82. https://doi.org/https://doi.org/10.1016/j.atmosres.2017.06.004

Stock, A., Haupt, A. J., Mach, M. E., & Micheli, F. (2018). Mapping ecological indicators of human impact with statistical and machine learning methods: Tests on the California coast. *Ecological Informatics*, *48*(March), 37–47. https://doi.org/10.1016/j.ecoinf.2018.07.007

Tabari, H., & Willems, P. (2023). Global risk assessment of compound hot-dry events in the context of future climate change and socioeconomic factors. *Npj Climate and Atmospheric Science*, *6*(1), 74. https://doi.org/10.1038/s41612-023-00401-7

Tam, T. Y. C., Sivarajkumar, S., Kapoor, S., Stolyar, A. V., Polanska, K., McCarthy, K. R., Osterhoudt, H., Wu, X., Visweswaran, S., Fu, S., Mathur, P., Cacciamani, G. E., Sun, C., Peng, Y., & Wang, Y. (2024). A framework for human evaluation of large language models in healthcare derived from literature review. *Npj Digital Medicine*, *7*(1), 258. https://doi.org/10.1038/s41746-024-01258-7

Tarolli, P., Luo, J., Straffelini, E., Liou, Y.-A., Nguyen, K.-A., Laurenti, R., Masin, R., & Vicenzo D'Agostino. (2023). Saltwater intrusion and climate change impact on coastal agriculture. *PLOS Water*, *2*(4), E0000121. https://doi.org/https://doi.org/10.1371/journal.pwat.0000121

Tarquini, S., Isola, I., Favalli, M., Mazzarini, F., Bisson, M., Pareschi, M. T., & Boschi, E. (2007). TINITALY/01: a new triangular irregular network of Italy. *Ann. Geophys.*, *50*, 407–425. http://www.annalsofgeophysics.eu/index.php/annals/article/view/4424

Tarquini, S., & Nannipieri, L. (2017). The 10 m-resolution TINITALY DEM as a trans-disciplinary basis for the

analysis of the Italian territory: Current trends and new perspectives. *Geomorphology*, *281*, 108–115. https://doi.org/https://doi.org/10.1016/j.geomorph.2016.12.022

Tárraga, J. M., Sevillano-Marco, E., Muñoz-Marí, J., Piles, M., Sitokonstantinou, V., Ronco, M., Miranda, M. T., Cerdà, J., & Camps-Valls, G. (2024). Causal discovery reveals complex patterns of drought-induced displacement. *IScience*, *27*(9), 110628. https://doi.org/https://doi.org/10.1016/j.isci.2024.110628

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

Tebaldi, C., Strauss, B. H., & Zervas, C. E. (2012). Modelling sea level rise impacts on storm surges along US coasts. *Environmental Research Letters*, *7*(1), 014032. https://doi.org/10.1088/1748-9326/7/1/014032

Teichert, N., Borja, A., Chust, G., Uriarte, A., & Lepage, M. (2016). Restoring fish ecological quality in estuaries: Implication of interactive and cumulative effects among anthropogenic stressors. *Science of the Total Environment*, *542*(Part A), 383–393. https://doi.org/https://doi.org/10.1016/j.scitotenv.2015.10.068

Terzi, S., Torresan, S., Schneiderbauer, S., Critto, A., Zebisch, M., & Marcomini, A. (2019). Multi-risk assessment in mountain regions: A review of modelling approaches for climate change adaptation. *Journal of Environmental Management*, *232*(February), 759–771. https://doi.org/https://doi.org/10.1016/j.jenvman.2018.11.100

Thulke, D., Gao, Y., Pelser, P., Brune, R., Jalota, R., Fok, F., Ramos, M., van Wyk, I., Nasir, A., Goldstein, H., Tragemann, T., Nguyen, K., Fowler, A., Stanco, A., Gabriel, J., Taylor, J., Moro, D., Tsymbalov, E., de Waal, J., … Erasmus, D. (2024). ClimateGPT: Towards AI Synthesizing Interdisciplinary Research on Climate Change. *Computer Science - Machine Learning*. http://arxiv.org/abs/2401.09646

Tilloy, A., Malamud, B. D., Winter, H., & Joly-Laugel, A. (2019). A review of quantification methodologies for multi-hazard interrelationships. *Earth-Science Reviews*, *September*, 102881. https://doi.org/https://doi.org/10.1016/j.earscirev.2019.102881

Tomasicchio, G. R., Salvadori, G., Lusito, L., Francone, A., Saponieri, A., Leone, E., & De Bartolo, S. (2022). A Statistical Analysis of the Occurrences of Critical Waves and Water Levels for the Management of the Operativity of the MoSE System in the Venice Lagoon. *Stochastic Environmental Research and Risk Assessment*, *36*(9), 2549–2560. https://doi.org/10.1007/s00477-021-02133-7

Torresan, S., Critto, A., Dalla Valle, M., Harvey, N., & Marcomini, A. (2008). Assessing coastal vulnerability to climate change: Comparing segmentation at global and regional scales. *Sustainability Science*, *3*(1), 45–65. https://doi.org/https://doi.org/10.1007/s11625-008-0045-1

Torresan, S., Critto, A., Rizzi, J., & Marcomini, A. (2012). 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 Science*. https://doi.org/10.5194/nhess-12-2347-2012

Torresan, S., Critto, A., Rizzi, J., Marcomini, A., Mendez, F. J., Leschka, S., & Fraile-Jurado, P. (2012). Assessment of coastal vulnerability to climate change hazards at the regional scale: the case study of the North Adriatic Sea. *Natural Hazards & Earth System Sciences*, *12*(7).

Torresan, S., Critto, A., Rizzi, J., Zabeo, A., Furlan, E., & Marcomini, A. (2016). DESYCO: A decision support system for the regional risk assessment of climate change impacts in coastal zones. *Ocean & Coastal Management*, *120*, 49–63. https://doi.org/https://doi.org/10.1016/j.ocecoaman.2015.11.003

Tosi, L., Da Lio, C., Bergamasco, A., Cosma, M., Cavallina, C., Fasson, A., Viezzoli, A., Zaggia, L., & Donnici, S. (2022). Sensitivity, Hazard, and Vulnerability of Farmlands to Saltwater Intrusion in Low-Lying Coastal Areas of Venice, Italy. *Water*, *14*(1), 64. https://doi.org/https://doi.org/10.3390/w14010064

Umgiesser, G., Bajo, M., Ferrarin, C., Cucco, A., Lionello, P., Zanchettin, D., Papa, A., Tosoni, A., Ferla, M., Coraci, E., Morucci, S., Crosato, F., Bonometto, A., Valentini, A., Orlić, M., Haigh, I. D., Nielsen, J. W., Bertin, X., Fortunato, A. B., … Nicholls, R. J. (2021). The

prediction of floods in Venice: methods, models and uncertainty (review article). *Natural Hazards & Earth System Sciences*, *21*(8), 2679–2704. https://doi.org/https://doi.org/10.5194/nhess-21-2679-2021

UNDP. (2010). Responding to climate change in small island developing states. In *United Nation Development Programme*.

UNDRR. (2017). *UNDRR: Terminology for Disaster Risk Reduction*. https://www.undrr.org/terminology (last access: 13 April 2022)

Vaghefi, S. A., Stammbach, D., Muccione, V., Bingler, J., Ni, J., Kraus, M., Allen, S., Colesanti-Senni, C., Wekhof, T., Schimanski, T., Gostlow, G., Yu, T., Wang, Q., Webersinke, N., Huggel, C., & Leippold, M. (2023). ChatClimate: Grounding conversational AI in climate science. *Communications Earth & Environment*, *4*(1), 480. https://doi.org/10.1038/s43247-023-01084-x

Van Der Borg, J. (1992). Tourism and Urban Development: The Case of Venice, Italy. *Tourism Recreation Research*, *17*(2), 46–56. https://doi.org/10.1080/02508281.1992.11014649

Vecere, A., Martina, M., Monteiro, R., & Galasso, C. (2021). Satellite precipitation–based extreme event detection for flood index insurance. *International Journal of Disaster Risk Reduction*, *55*, 102108. https://doi.org/https://doi.org/10.1016/j.ijdrr.2021.102108

Verrelle, A., Glinton, M., Bazile, E., Le Moigne, P., Randriamampianina, R., Ridal, M., Berggren, L., Undén, P., Schimanke, S., Mladek, R., & Soci, C. (2022). *CERRA-Land sub-daily regional reanalysis data for Europe from 1984 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS).* https://doi.org/https://doi.org/10.24381/cds.a7f3cd0b

Vuuren, D. P. van, Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G. C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S. J., & Rose, S. K. (2011). The representative concentration pathways: an overview. *Climatic Change*, *109*(5). https://doi.org/https://doi.org/10.1007/s10584-011-0148-z

Wahl, T., Haigh, I. D., Nicholls, R. J., Arns, A., Dangendorf, S., Hinkel, J., & Slangen, A. B. A. (2017). Understanding extreme sea levels for broad-scale coastal impact and adaptation analysis. *Nature Communications*, *8*, 16075. https://doi.org/https://doi.org/10.1038/ncomms16075

Wang, Y., Song, Q., Du, Y., Wang, J., Zhou, J., Du, Z., & Li, T. (2019). A random forest model to predict heatstroke occurrence for heatwave in China. *Science of the Total Environment*, *650*, 3048–3053. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.09.369

Wang, J., & Yan, Z. (2021). Rapid rises in the magnitude and risk of extreme regional heat wave events in China. *Weather and Climate Extremes*, *34*, 100379. https://doi.org/10.1016/j.wace.2021.100379

Wang, R., Mi, F., Chen, Y., Xue, B., Wang, H., Zhu, Q., Wong, K.-F., & Xu, R. (2024). Role Prompting Guided Domain Adaptation with General Capability Preserve for Large Language Models. *Computer Science - Computation and Language*. https://doi.org/https://doi.org/10.48550/arXiv.2403.02756

Ward, P. J., Daniell, J. E., Duncan, M., Dunne, A., Hananel, C., Hochrainer-Stigler, S., Tijssen, A., Torresan, S., Ciurean, R., Gill, J. C., Sillmann, J., Couasnon, A., Koks, E., Padrón-Fumero, N., Tatman, S., Lund, M. T., Adesiyun, A., Aerts, J. C. J. H., Alabaster, A., … de Ruiter, M. C. (2022). Invited perspectives: A research agenda towards disaster risk management pathways in multi-(hazard-)risk assessment. *Nat. Hazards Earth Syst. Sci.*, *22*, 1487–1497. https://doi.org/https://doi.org/10.5194/nhess-22-1487-2022

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Ichter, B., Xia, F., Chi, E., Le, Q., & Zhou, D. (2022). Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. *Computer Science - Computation and Language*. https://doi.org/https://doi.org/10.48550/arXiv.2201.11903

Weilnhammer, V., Schmid, J., Mittermeier, I., Schreiber, F., Jiang, L., Pastuhovic, V., Herr, C., & Heinze, S. (2021). Extreme weather events in europe and their health consequences – A systematic review. *International Journal of Hygiene and Environmental Health*, *233*, 113688. https://doi.org/10.1016/j.ijheh.2021.113688

Weiskopf, S. R., Rubenstein, M. A., Crozier, L. G., Gaichas, S., Griffis, R., Halofsky, J. E., Hyde, K. J. W., Morelli, T. L., Morisette, J. T., Muñoz, R. C., Pershing, A. J., Peterson, D. L., Poudel, R., Staudinger, M. D., Sutton-

Grier, A. E., Thompson, L., Vose, J., Weltzin, J. F., & Whyte, K. P. (2020). Climate change effects on biodiversity, ecosystems, ecosystem services, and natural resource management in the United States. *Science of the Total Environment*, *xxxx*. https://doi.org/10.1016/j.scitotenv.2020.137782

Ying, X. (2019). An Overview of Overfitting and its Solutions. *Journal of Physics: Conference Series*, *1168*(2). https://doi.org/10.1088/1742-6596/1168/2/022022

Yousefi, N., Alaghband, M., & Garibay, I. (2019). *A Comprehensive Survey on Machine Learning Techniques and User Authentication Approaches for Credit Card Fraud Detection*. https://doi.org/https://doi.org/10.48550/arXiv.1912.02629

Zanchettin, D., Bruni, S., Raicich, F., Lionello, P., Adloff, F., Androsov, A., Antonioli, F., Artale, V., Carminati, E., Ferrarin, C., Fofonova, V., Nicholls, R., Rubinetti, S., Rubino, A., Sannino, G., Spada, G., Thiéblemont, R., Tsimplis, M., Umgiesser, G., … Zerbini, S. (2020). Review article: Sea-level rise in Venice: historic and future trends. *Natural Hazards and Earth System Sciences Discussions*, *November*, 1–56. https://doi.org/10.5194/nhess-2020-351

Zanuttigh, B., Simcic, D., Bagli, S., Bozzeda, F., Pietrantoni, L., Zagonari, F., Hoggart, S., & Nicholls, R. J. (2014). THESEUS decision support system for coastal risk management. *Coastal Engineering*, *87*, 218–239. https://doi.org/10.1016/j.coastaleng.2013.11.013

Zennaro, F., Furlan, E., Melaku Canu, D., Aslan, S., Solidoro, C., & Critto, A. (2023). Evaluation of lagoon eutrophication potential under climate change conditions: A novel water quality machine learning and biogeochemical-based framework. *EGU General Assembly 2023*, 24–28 Apr 2023, EGU23-8409. https://doi.org/https://dx.doi.org/10.5194/egusphere-egu23-8409

Zennaro, F., Furlan, E., Simeoni, C., Torresan, S., Aslan, S., Critto, A., & Marcomini, A. (2021). Exploring machine learning potential for climate change risk assessment. *Earth-Science Reviews*, *220*, 103752. https://doi.org/10.1016/J.EARSCIREV.2021.103752

Zheng, H. S., Mishra, S., Chen, X., Cheng, H.-T., Chi, E. H., Le, Q. V, & Zhou, D. (2023). Take a Step Back: Evoking Reasoning via Abstraction in Large Language Models. *Computer Science - Machine Learning*. https://doi.org/https://doi.org/10.48550/arXiv.2310.06117

Zonn, I. S., Kostianoy, A. G., Semenov, A. V., Joksimović, A., & Đurović, M. (2021). *Veneto* (pp. 363–364). https://doi.org/10.1007/978-3-030-50032-0_604

Zschau, J. (2017). Where are we with multihazards, multirisks assessment capacities? In *Science for Disaster Risk Management 2017* (pp. 98–115). https://drmkc.jrc.ec.europa.eu/portals/0/Knowledge/ScienceforDRM/ch02/ch02_subch0205.pdf

Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., Hurk, B. van den, AghaKouchak, A., Jézéquel, A., Mahecha, M. D., Maraun, D., Ramos, A. M., Ridder, N. N., Thiery, W., & Vignotto, E. (2020). A typology of compound weather and climate events. *Nature Reviews Earth & Environment*, *1*, 333–347. https://doi.org/https://doi.org/10.1038/s43017-020-0060-z