NBRACER
Nature Based Solutions
for Atlantic Regional Climate Resilience

HORIZON Europe Research and Innovation actions in support of the implementation of the Adaptation to Climate Change Mission
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Guideline to build scenarios for the assessment of NbS efficiency

Deliverable D5.2

Version n° 4

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About NBRACER

The impacts of climate change on people, planet and prosperity are intensifying. Many regions and communities are struggling to avoid losses and need to step up the effort to increase their climate resilience. Ongoing natural capital degradation leads to growing costs, increased vulnerability, and decreased stability of key systems. Whilst there has been noticeable progress and inspiring examples of adaptation solutions in Europe, the pressure to make rapid and visible progress has often led to a focus on stand-alone, easy-to-measure projects that tackle issues through either direct or existing policy levers, or sector-by-sector mainstreaming. But the dire trends of climate change challenge Europe, and its regions, needs exploration of new routes towards more ambitious and large-scale systemic adaptation. The European Mission on Adaptation to Climate Change (MACC) recognizes the need to adopt a systemic approach to enhance climate adaptation in EU regions, cities, and local authorities by 2030 by working across sectors and disciplines, experimenting, and involving local communities.

NBRACER contributes to the MACC by addressing this challenge with an innovative and practical approach to accelerating the transformation towards climate adaptation. Transformation journeys will be based on the smart, replicable, scalable, and transferable packaging of Nature-based Solutions (NbS) rooted in the resources supplied by biogeographic landscapes while closing the NbS implementation gap. Regions are key players of this innovative action approach aiming at developing, testing, and implementing NbS at systemic level and building adaptation pathways supported by detailed and quantitative analysis of place-specific multi-risks, governance, socio-economic contexts, and (regional) specific needs.

NBRACER works with 'Demonstrating' and 'Replicating' regions across three different Landscapes (Marine & Coastal, Urban, Rural) in the European Atlantic biogeographical area to vision and co-design place based sustainable and innovative NbS that are tailor-made within the regional landscapes and aligned with their climate resilience plans and strategies. The solutions are upscaled into coherent regional packages that support the development of time and place specific adaptation pathways combining both technological and social innovations. The project is supporting, stimulating, and mainstreaming the deployment of NbS beyond the NBRACER regions and across biogeographical areas.

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Abbreviations and acronyms

Acronym	Description
AI	Artificial Intelligence
BN	Bayesian Networks
CRI	Climate Risk Index
ESS	Ecosystem service
IPCC	International Panel on Climate Change
KCS	Key Community System
ML	Machine Learning
NbS	Nature-based solutions
P2R	Pathways to Resilience
RF	Random Forest
SoS	System of Systems
WP	Work Package

Summary

The NBRACER deliverable D5.2, entitled ”Guideline to Build Scenarios for the Assessment of NbS Efficiency" was written in response to Work Package 5 “Technical framework supporting the design and implementation of NbS”, task 5.2 “Building climate risk scenarios for decision making”. Broadly, this document outlines methodologies and best practices for assessing Nature-based Solutions (NbS) in building climate adaptation strategies while utilising the "Pathways to Resilience" (P2R) Framework for Resiliency. The guideline emphasizes creating tailored scenarios for evaluating NbS efficiency in diverse landscapes, including marine, coastal, urban, and rural contexts. It integrates climate risk assessment and scenario-building frameworks, utilizing concepts from the IPCC's fifth assessment report (AR5) and sixth assessment report (AR6), which define risk components such as hazard, vulnerability, exposure and response. The deliverable serves as a resource for regional stakeholders to align local needs with data-driven decision-making processes, ensuring equitable access to knowledge and promoting scalable adaptation pathways.

Specifically, the guideline introduces three modelling approaches — index-based, probabilistic and Machine Learning (ML) models—to accommodate varying data availability and regional capabilities. Each model is described with implementation steps and suitability based on regional needs, highlighting the balance between accessibility and precision. Index-based model offers a broad overview for policy-making, probabilistic models are suitable for complex interdependent systems, and ML provides high-detail analysis for data-intensive scenarios. By integrating these tools into the NBRACER framework, the project seeks to create resilient, data-informed strategies to address the growing risks of climate change and support regions in developing effective and sustainable adaptation measures.

Keywords

Climate change, risk assessment methodology, nature-based solutions, scenario analysis

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1. Setting the Scene: the NBRACER approach

NBRACER adopts a flexible and scalable operational approach, utilizing eight Work Packages (WPs) that align with specific activities across the P2R Framework and related steps. This structured alignment ensures that resilience-building moves from general assessments to localized, fine-tuned strategies, enabling regions to enhance their capacity for climate resilience effectively. Figure 1 shows this scheme more widely however in the subsequent paragraphs, the connections of NBRACER WP5 tasks and associated deliverables will be contextualized within both the wider P2R framework as well as other WPs within the NBRACER project (such as where WP5 extensions, collaborations, and results will be carried onward).

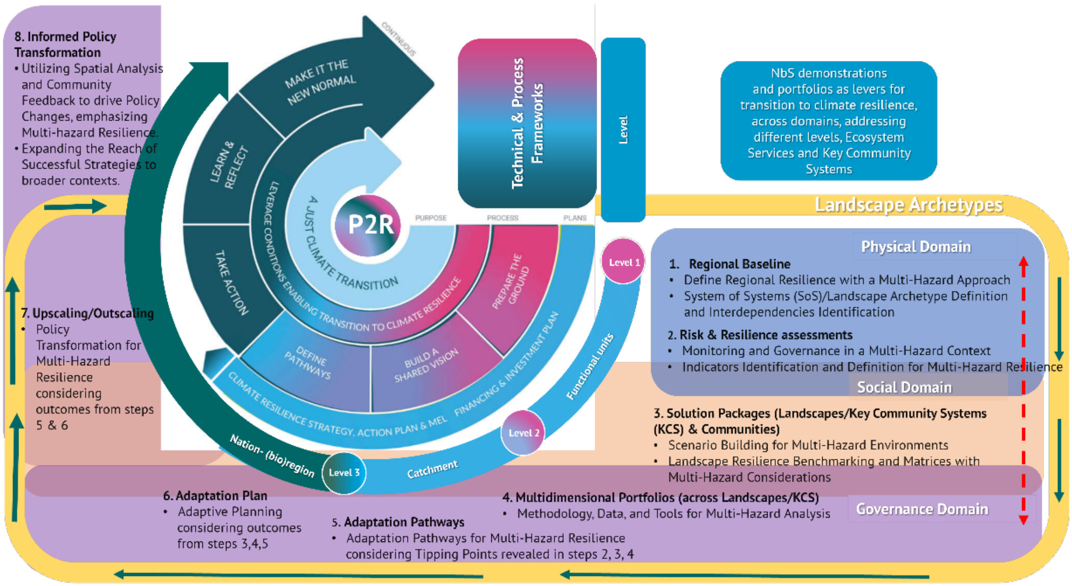

Figure 1: Overview of the NBRACER approach with 8 steps, elaborating an iterative process for achieving a just climate transition through multi-level planning.

1.1 WP5 within NBRACER

In the current deliverable, Work Package 5 "Technical framework supporting the design and implementation of NbS", or WP5, is highlighted (Figure 2). The main goal of WP5 is to build a conceptual, analytical, and operational framework for the different landscapes and key community systems (KCSs) that allows generating the required climatic and ecological information at the appropriate hierarchical level to assist in the selection, design and implementation of NbS.

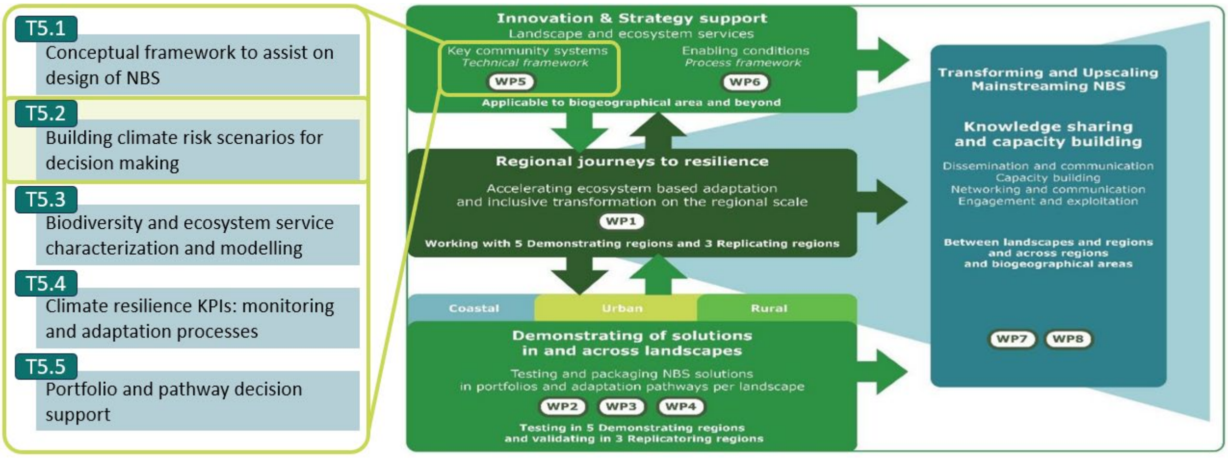

Figure 2: Work package 5 within the NBRACER project and overview of the different WP5 tasks. Task 5.2 is highlighted, as it frames Deliverable 5.2 which is reported here. This work package is organized across 5 component tasks (T5.1-T5.5, left panel).

These tasks are reproduced from the NBRACER grant agreement and details listed below are component milestones, lead beneficiaries, and participants included for contextual usage only:

- *Task 5.1. Developing the conceptual framework to assist on the design of NbS (M1– M24) Lead: FIHAC; Participants: Deltares, CKIC, WR, Tecnalia, Cantabria Uni, VITO*
- *Task 5.2. Building climate risk scenarios for decision making (M1– M24) Lead: CMCC; Participants: Cantabria Uni, Deltares, Tecnalia*
- *Task 5.3. Biodiversity and ecosystem service characterization and modelling (M3– M30) Lead: Cantabria Uni; Participants: Deltares, FIHAC, VITO, CMCC*
- *Task 5.4. Climate Resilience KPIs: monitoring adaptation processes (M3 – M30) Lead: Tecnalia; Participants: Deltares, CKIC, WR, Cantabria Uni, VITO*
- *Task 5.5 Portfolio and Pathway decision support (M6– M48) Lead: Deltares; Participants: WR, Tecnalia, FIHAC, Cantabria Uni, CMCC*

Below, the NBRACER suggested steps displayed graphically within Figure 2 are harmonized with specific actions to the P2R framework, as displayed in Figure 1. The attention of the reader is drawn to WP5, and how its tasks (mentioned above) crosscut both the P2R framework and NBRACER WPs, building results for climate resilience in the context of NBRACER's "coarse to fine scale" methodology.

Step 1: Establish a Regional Baseline

- **Defining Regional Resilience**: Establish resilience baselines using a multi-hazard approach, integrating spatial data to map KCS and their interdependencies.
- *WP Alignment*: **WP1** (Regional Baselines, Task 1.1), **WP5** (Conceptual Framework, Task 5.1), **WP6** (Transformative Capacity), **WP7** (Capacity Building for NbS Upscaling).

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- **Outcome**: A foundational understanding of the region's structure, highlighting where risks and solutions can interact.

Step 2: Risk and Resilience Assessments

- **Identify and Assess Multi-Hazard Risks**: Evaluate potential hazards and their spatial interactions with KCS to develop comprehensive risk scenarios.
    - *WP Alignment*: **WP5** (Building Climate Risk Scenarios, Task 5.2; Climate Resilience KPIs, Task 5.4).
    - *Scale Level*: **Level 1 (Physical Landscape)** – Interaction between single hazards and NbS in functional units and **Level 2 (Social Landscape)** – Multiple climate hazards – multiple NbS in a catchment
- **Outcome**: A detailed, spatial and temporal risk profile to guide NbS interventions.

Step 3: Solution Packages (Landscapes/KCS)

- **Develop Scenario-Based Solutions**: Create multi-hazard resilience packages by engaging communities and testing NbS solutions for effectiveness under several scenarios.
    - *WP Alignment*: **WP1** (Demonstration Framing, Task 1.2), **WP5** (Decision Support for Portfolio/Pathways, Task 5.5), **WP6** (Inclusive Strategies, Governance Models, NbS Tools).
    - *Scale Level*: **Level 2 (Social Landscape)** – Understanding hazard impacts on social systems and KCS.
- **Outcome**: A multi-layered portfolio of solutions adapted to the region's needs.

Step 4: Creating a Multi-Dimensional Portfolio

- **Develop Portfolios Across Landscapes/KCS**: Integrate methodologies, tools, and data for resilience across physical, social, and governance layers.
    - *WP Alignment*: **WP1**, **WP5**, **WP6**, and **WP8** (Engagement and Exploitation) support tool development.
    - *Scale Level*: **Level 3 (Governance Landscape)** – Multi-scale interactions for broader regional strategies.
- **Outcome**: A multi-layered portfolio supporting both short-term interventions and long-term resilience planning.

Step 5: Designing Adaptation Pathways

- **Flexible Pathways for Resilience**: Define pathways that consider tipping points and changing conditions to adapt policies and strategies according to various scenarios.
    - *WP Alignment*: **WP5** (Task 5.3 Biodiversity Characterization, Task 5.5 Pathway Decision Support), **WP6** (Governance Models), **WP7** (Capacity Building Program).
    - *Scale Level*: **Levels 2 (Social Landscape) & 3 (Governance Landscape)** – Integrating social resilience mechanisms and governance models.

- **Outcome**: A set of adaptive pathways, with options for short-term and long-term resilience planning, based on feedbacks and community participation.

Step 6: Formulating an Adaptation Plan

- **Developing and Testing Plans**: Frame adaptive plans based on NbS solution packages, validate in demonstration regions, and incorporate community feedback.
  - o *WP Alignment*: **WP1** (Mainstreaming NbS), **WP5** (Monitoring and KPIs), **WP6** (Governance Strategies)
- **Outcome**: An operational adaptation plan for regional resilience.

Step 7: Upscaling/Outscaling Strategies

- **Scaling Solutions Across Regions**: Leverage successful resilience strategies and policies to expand solutions across larger landscapes and governance scales.
  - o *WP Alignment*: **WP1** (Evaluating and Connecting Regions), **WP5** (Task 5.4 KPIs, Task 5.5 Portfolio Support), **WP6** (Policy Development), **WP8** (Communication).
  - o *Scale Level*: **Levels 2 (Social Landscape) & 3 (Governance Landscape)** – Multi-scale strategy implementation.
- **Outcome**: A strategy to expand successful NbS, ensuring widespread impact across regions.

Step 8: Informed Policy Transformation

- **Adaptation Through Policy:** Use spatial analysis, feedback loops, and scenario outcomes to drive policy changes and resilience adaptation.
  - o *WP Alignment*: **WP1** (Policy Evaluation), **WP5** (Climate Resilience KPIs), **WP6** (Policy Good Practices), **WP7** (Product Packaging), **WP8** (Dissemination and Networking).
- **Outcome**: Inclusive policy transformations that ensure NbS are integrated into broader climate adaptation strategies.

Taken together, the tasks comprising WP5 will contribute to assessing risks, developing monitoring processes, and solution packages, and supporting adaptation pathways. Within NBRACER, WP5 serves as a lynchpin within the resilience journey by helping to establish a baseline (or baseline assessment) for the regions to then progress towards solutions development. In the following sections, we will discuss Task 5.2, as it pertains to this current deliverable.

1.2 Task 5.2 “Building climate risk scenarios for decision making”

Task 5.2, entitled “Building climate risk scenarios for decision making” will take place from project initiation in month 1 until month 24 of the project when its component deliverable, D5.2 discussed below, is due to project partners. This task is led by CMCC with subsequent collaboration and participation from the following partners: Cantabria Uni, Deltares, and Tecnalia.

Task 5.2 was charged with scenario building, which is a key part of decision-making processes when designing solutions for climate risk adaptation. In order to build the most complete picture of climate scenarios, these would ideally include the most reliable hydro-climatic and socioeconomic data-driven regional and/or local contexts (e.g., ERA5 products). These are then used to evaluate the associated climate risks and the effectiveness of present and future solutions to be implemented.

Under this task, a portfolio of methodological procedures are presented to develop NbS implementation scenarios at different scales and under different data availability contexts. Building off D5.1 (block A, Figure 3), the approaches will include climate and land-use land cover dynamics as both spheres are heavily intertwined to reduce and/or amplify climate change risks (e.g., floods, heatwaves, droughts, etc…).

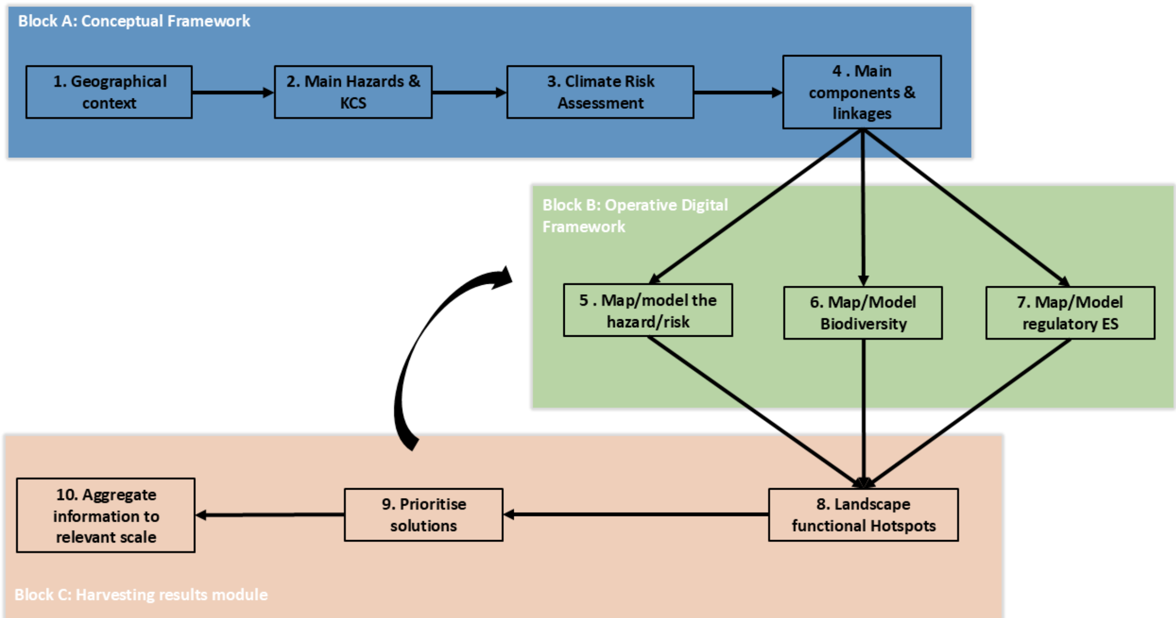

Figure 3: A flow chart broadly outlining the continuity between the NBRACER Conceptual Framework, Operative Digital Framework, and finally, the harvest of model results.

This work will be linked to landscapes, with particular attention given to analyzing the effects on the KCSs in each context, adopting a multi-perspective approach of key sectors (e.g., water-energy-food nexus). For a more detailed discussion on KCSs and how this concept is built into the NBRACER approach, readers are referred to D5.1: "Developing the conceptual framework to assist on the design of Nature Based Solutions".

1.3 Deliverable D5.2 "Guideline to build scenarios for the assessment of NBS efficiency"

Task 5.2 culminates in its associated deliverable, Deliverable 5.2 entitled, "Guideline to build scenarios for the assessment of NBS efficiency". The document will be a non-technical set of steps and best practices that can be utilized by NBRACER project partners to guide their assessment process. Amended throughout will be links to scientific publications for more technically focused stakeholders. The guide will present up to three data-based methodologies that regional stakeholders may choose as they prepare their investigation of NbS efficiency at their regional level. The aforementioned data-based methodologies, also referred to as the "data-based approach", will cover assessment "pipelines" that are determined chiefly by the resources available at the regional level, thus ensuring an assessment that is tailored to the needs and visions of the stakeholders.

1.3.1 Why are the guidelines needed?

These guidelines are needed to ensure there is equitable access to knowledge across the NBRACER project, regardless of technical ability, technical knowledge, or otherwise. In this way, the guidelines offer a common ground and base of understanding across the NBRACER project. From this base, the primary purpose of these guidelines is to facilitate regional stakeholders in developing risk assessment at different scales and under different data availability contexts, which serves as a foundational step for these stakeholders in building NbS implementation scenarios.

More specifically, these guidelines serve as one of the many direct linkages between the NBRACER project's system of system (SoS) approach with the P2R Resilience Journey framework, in particular Step 2 (risk and resilience assessments) and Step 8 (Informed policy transformation) (Figure 1). Inherent in the SoS approach, is the transition from coarse to fine-grained resolution when tailoring responses. In this way the guidelines will help regional stakeholders impactfully move through the process of scenario building and implementing resilience strategies by acknowledging their respective needs (by beginning to bridge both biophysical and social components) that are integrated into subsequent steps; namely Step 3 Solution packages with the outcome being a "multi-layered portfolio of solutions adapted to the region's needs" (Figure 1).

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1.3.2 Where will it be applied?

Deliverable 5.2 will be applied as part of the cross-cutting deliverables generated from the products of other NBRACER WPs. Most immediately, regional stakeholder identification, visioning, and stocktaking identified as part of Work Package 1 "Regional journeys to resilience: integrated stocktaking, visioning and prioritising" informs the work and products that WP5 will develop (Figure 1). In particular, D.5.2 will be applied within the conceptual framework developed as part of T5.1 "Developing the conceptual framework to assist on the design of NBS" (Figure 3). Of particular interest in the conceptual framework, the regions will find landscape archetypes (based upon their responses to the NBRACER baseline questionnaire) that will provide an initial pass at understanding and making sense of the complex, heterogeneous landscapes at the regional level. Secondly, KCSs will be codified (again, primarily identified through the NBRACER baseline questionnaire), allowing the region to identify which sectors climate hazards will ultimately impact and which they would like to focus their adaptation or mitigation efforts on. All told, this serves to integrate these systems into the proposed modelling/risk assessment work of the project.

1.3.3 Who is involved?

As no two regions are the same, it is intended that the Regional Coordinators interested in mapping regional risk will identify the intended users and stakeholders for this deliverable. At large, intended users should be familiar with the Region's vision for climate adaptation and be able to source potential collaborators to aid in the identification of inputs that will be incorporated into their respective data-based approach pipeline. Intended users will be those stakeholders who will be decision-makers in the region across both technical and non-technical perspectives. Examples may include, but are not limited to: academic or knowledge-driven institutions (such as universities, research centres, think tanks), private consulting firms (across STEM and financial sectors), regional/municipal/local government staff, and local NGOs. It is anticipated that the stakeholder mapping and identification task and products, such as the NBRACER baseline questionnaire and other products originating from WP6, will streamline this process substantially.

1.3.4 Intended use of Guidelines by partners

These guidelines will serve as a resource for local, and regional stakeholders to determine the efficiency within local NbS implementation actions. This resource should be used by those stakeholders responsible for, but not limited to, those completing data sourcing/collecting and model building. These stakeholders may be based at the regional level, or those consultants working on behalf and representing the interests, of regional stakeholders. In NBRACER, partners with technical expertise in this field will conduct the first-pass analyses: in particular, Cantabria

University in Cantabria (Spain), VITO in Ostend (West Flanders), and CMCC in another NBRACER case study. However, since not all project partners possess own technical capacities, targeted capacity-building activities will be organized to overcome this challenge.

2. Background primer on Risk Assessment

Risk assessment is a fundamental component in various fields, including environmental management, health and safety, and organizational operations. It involves identifying potential risks, analysing their impacts, and determining appropriate measures to mitigate them.
This chapter provides an in-depth review of the overall process behind risk assessment as it applies to climate risk assessment, focusing on the ISO standards 14091, 31010 and 31000 (Table 1). These standards provide a robust framework (Figure 4) for conducting climate risk assessments, which are crucial for effective decision-making and strategic planning.

Table 1: Comparisons between ISO Standards and their usages within climate risk assessment

ISO standards	**Description**
ISO 14091 - Adaptation to Climate Change – Vulnerability, Impacts and Risk Assessment	Offers guidelines for assessing the risk and vulnerabilities related to climate change. This standard emphasizes the need for adaptive measures to mitigate these impacts and enhance resilience. It provides a systematic approach to identifying and evaluating the impacts of climate change on organizations and communities, crucial for informed adaptation planning and implementation.
ISO 31000 - Risk Management – Guidelines	Provides a broad framework for risk management, applicable to any organization regardless of its size, industry, or sector. It emphasizes the importance of integrating risk management and organizational governance, strategy, and planning.
ISO 31010 - Risk Management – Risk Assessment Techniques	Complements ISO 31000 by providing a range of risk assessment techniques. It is a comprehensive guide that outlines various methods and tools for identifying, analyzing, and evaluating risk. This standard is widely applicable across different sectors and can be tailored to specific organizational needs.

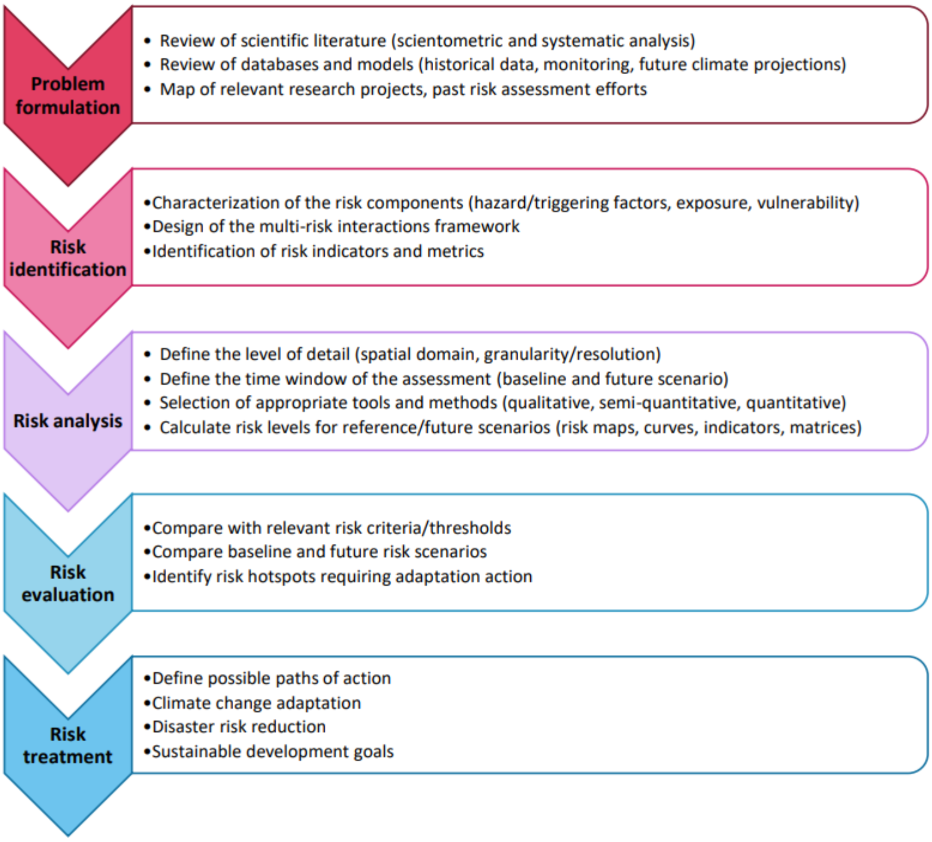

Figure 4: Stages describing the process for multi-risk assessment to be utilized in the study. Figure adopted for use from the ISO Standard 31010.

2.1 Main risk concepts and terminologies

This section will introduce and explain key risk concepts from the *Intergovernmental Panel on Climate Change* (IPCC) AR5 and AR6. It will outline the components of the risk assessment procedure: hazard, exposure, vulnerability, and response. Additionally, it will introduce new AR6 concepts such as multi-risk, compound, and cascading risks. Input figures will highlight risk at the centre, drawing from IPCC reports (Figure 5). The section will also discuss the integration of "resilience" into these concepts. In the frame of the NBRACER project, the standardized IPCC terminologies concerning risk and risk assessment framework to follow were first presented to regional representatives within the "Connecting NBRACER" webinar series, held on November 19th, 2024. During this online meeting, regional representatives were exposed to such terminologies to assess their comprehension of this specific topic through an evaluation conducted via a Mentimeter[1] survey (Annex 1). They were also informed that a similar evaluation would take place during the upcoming Connecting NBRACER webinar series, when the finalized

[1] **Mentimeter** is an interactive platform for live polls, quizzes, and Q&A sessions. Participants join with a unique code, and results are displayed instantly in an engaging, visual format (https://www.mentimeter.com/).

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deliverable and its associated products would be presented. This approach allows the consortium to monitor regional capacity building, assess progress in knowledge acquisition, and identify areas where additional resources or support may be required to enhance regional expertise effectively.

Table 2: Definitions underpinning multi hazard risk assessment as defined by Intergovernmental Panel on Climate Change (IPCC) within the Sixth Assessment Reports (AR6; IPCC 2023).

Term	Definition
Risk	As the potential for adverse consequences for human or ecological systems, recognising the diversity of values and objectives associated with such systems. In the context of climate change, risks can arise from potential impacts of climate change as well as human responses to climate change. Relevant adverse consequences include those on lives, livelihoods, health and well-being, economic, social and cultural assets and investments, infrastructure, services (including ecosystem services), ecosystems and species. In the context of climate change impacts, risks result from dynamic interactions between climate- related hazards with the exposure and vulnerability of the affected human or ecological system to the hazards. Hazards, exposure and vulnerability may each be subject to uncertainty in terms of magnitude and likelihood of occurrence, and each may change over time and space due to socio-economic changes and human decision-making (see also risk management, adaptation and mitigation). In the context of climate change responses, risks result from the potential for such responses not achieving the intended objective(s), or from potential trade-offs with, or negative side-effects on, other societal objectives, such as the Sustainable Development Goals (SDGs) (see also risk trade-off). Risks can arise, for example, from uncertainty in implementation, effectiveness or outcomes of climate policy, climate-related investments, technology development or adoption, and system transitions.
Hazard	The potential occurrence of a natural or human-induced physical event or trend that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems and environmental resources.
Exposure	The presence of people; livelihoods; species or ecosystems; environmental functions, services, and resources; infrastructure; or economic, social, or cultural assets in places and settings that could be adversely affected.
Vulnerability	The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt.

Term	Definition
Adaptation options	The array of strategies and measures that are available and appropriate for addressing adaptation. They include a wide range of actions that can be categorised as structural, institutional, ecological or behavioural.
Compound risks	Arise from the interaction of hazards, which may be characterised by single extreme events or multiple coincident or sequential events that interact with exposed systems or sectors.
Impacts	The consequences of realized risks on natural and human systems, where risks result from the interactions of climate-related hazards (including extreme weather/climate events), exposure, and vulnerability. Impacts generally refer to effects on lives, livelihoods, health and well-being, ecosystems and species, economic, social and cultural assets, services (including ecosystem services), and infrastructure. Impacts may be referred to as consequences or outcomes and can be adverse or beneficial.
Risk management	Risk management is defined as plans, actions, strategies or policies to reduce the likelihood and/or magnitude of adverse potential consequences, based on assessed or perceived risks. {1.2.1, Annex II: Glossary}
Adaptation	Adaptation in this report is defined, in human systems, as the process of adjustment to actual or expected climate and its effects in order to moderate harm or exploit beneficial opportunities. In natural systems, adaptation is the process of adjustment to actual climate and its effects; human intervention may facilitate this (see Annex II: Glossary).
Resilience	Resilience in this report is defined as the capacity of social, economic and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganising in ways that maintain their essential function, identity and structure while also maintaining the capacity for adaptation, learning and transformation. Resilience is an entry point commonly used, although under a wide spectrum of meanings. Resilience as a system trait overlaps with concepts of vulnerability, adaptive capacity and, thus, risk, and resilience as a strategy overlaps with risk management, adaptation and transformation. Implemented adaptation is often organised around resilience as bouncing back and returning to a previous state after a disturbance. {1.2.1, Annex II: Glossary}

Climate change is accelerating and intensifying slow and rapid onset events across all environments. To develop effective strategies for mitigating these impacts, it is crucial to first characterize all key components interplaying in the risk definition, including **hazard, exposure, vulnerability,** and **response**. This step is fundamental to understanding how each socio-ecological system is featured and its ability to cope with climate change, thus developing an integrated framework to assess risks.

A comprehensive description of these key components is here provided highlighting their evolution across the assessment reports as released by the IPCC and the related scientific literature. Over the past decades, the IPCC has produced several reports[2] as part of a global and collective effort to gather all knowledge on climate change, its causes, potential impacts and response options. A total of six assessments have been produced with the latest being the AR6, released between 2021 and 2023.

The definitions of hazard, exposure, vulnerability and risk were significantly expanded in the AR5 which emphasised their broader implications for climate change impacts (IPCC, 2014). AR5 expanded the concept of hazard to include "physical impacts," emphasising climate-related events or trends with potential adverse effects on human and ecological systems, while broadening the definition of exposure to include species, ecosystems, and environmental functions. Moreover, the AR5 expanded the definition of vulnerability as well to emphasise its complexity and multidimensionality. All these changes were maintained in the AR6 which defined them as follows:

(a) **hazards** as natural or human-induced events or trends that can cause damage to social and ecological systems;

(b) **exposure** refers to the presence of human and ecological elements in vulnerable settings;

(c) **vulnerabilit**y is the propensity to be adversely affected, encompassing sensitivity to harm and the capacity to cope and adapt; and

(d) **risk** is defined as the probability of adverse consequences for human or ecological systems due to climate change and human responses to it.

It is in the latest AR6 that the concept of **multi-risk**, including **compound** and **cascading risks** was introduced (Figure 6), providing a more detailed and integrative perspective on how various risk factors interact and influence each other (IPCC, 2023). In particular, the report places a stronger emphasis on risk and solutions than previous reports (IPCC, 2023). Since the Special Report on Global Warming of 1.5°C in 2014, efforts have been made across Working Groups to develop a consistent risk framing for the IPCC's AR6 (Reisinger *et al*., 2020). This comprehensive framing spans all three Working Groups, considering risks from climate change responses, dynamic and cascading effects, and detailed geographic impacts on people and ecosystems. This new framework, as reported in the AR6, highlights the connections between climate responses,

[2] https://www.ipcc.ch/ Special and Methodology Reports

sustainable development, and transformation, as well as the governance implications for both the public and private sectors (IPCC, 2023).

The construction of the multi-hazard interactions framework enhances cross-institutional dialogue on multi-hazards interactions and their potential impacts (Gill *et al.*, 2020). Such frameworks can facilitate a deeper understanding of how different hazards interact with each other, leading to cascading effects and compounding risk.

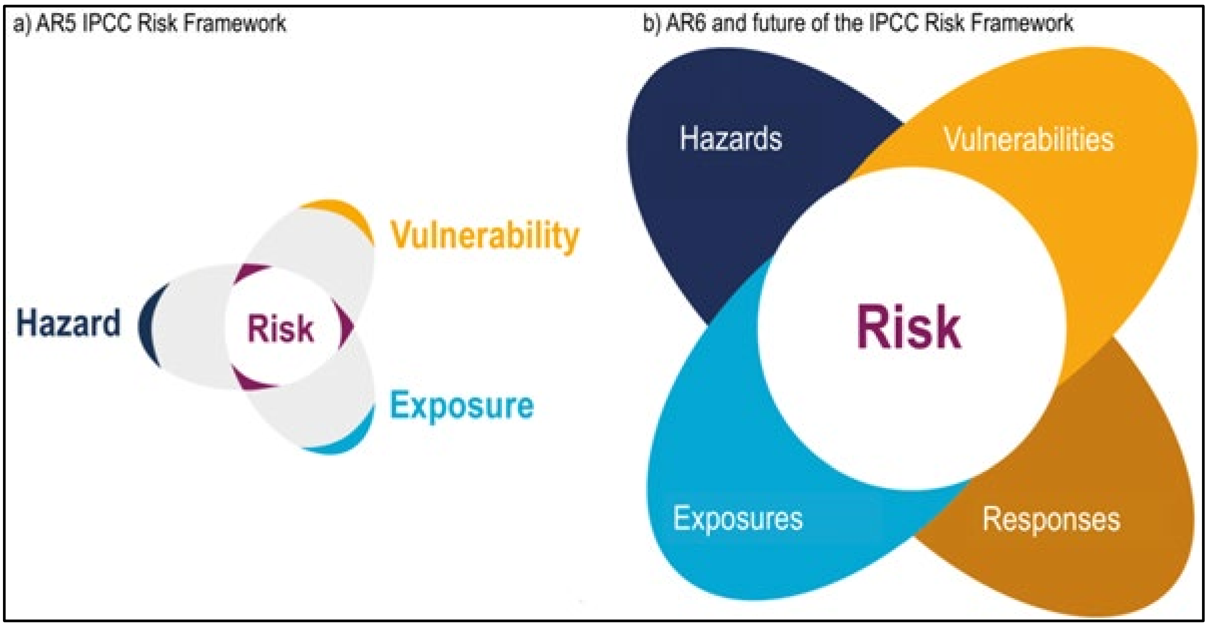

Figure 5: Evolution of the risk frameworks developed by the Intergovernmental Panel on Climate Change (IPCC) within the Fifth and Sixth Assessment Reports (AR5 and AR6; IPCC, 2014; 2023).

In addition to hazard, exposure and vulnerability, AR6 introduces for the first time in the risk framework **(e) responses** as part of the main components of climate change risk (Figure 5). Including response in risk assessment enhances the understanding of the relationship between climate change risk and **resilience**, as responses are crucial for governance and understanding feedback that shapes social-ecological systems (Simpson *et al.*, 2021). Considering response as a determinant of risk supports integrating climate-resilient development pathways and climate change risk concepts within assessments. Risk can emerge from various pathways shaped by interacting drivers. Understanding potential outcomes and their severity necessitates recognising this web of interactions stemming from anthropogenic climate change or human-induced events and pressures. These changes mark a significant advancement in understanding and addressing the complexities of climate change impacts. Despite numerous initiatives tackling this issue (Dal Barco *et al.*, 2024; Furlan *et al.*, 2019; Gallina *et al.*, 2016; IPCC, 2014; Terzi *et al.*, 2019), there is no unified framework for assessing complex climate change risks.

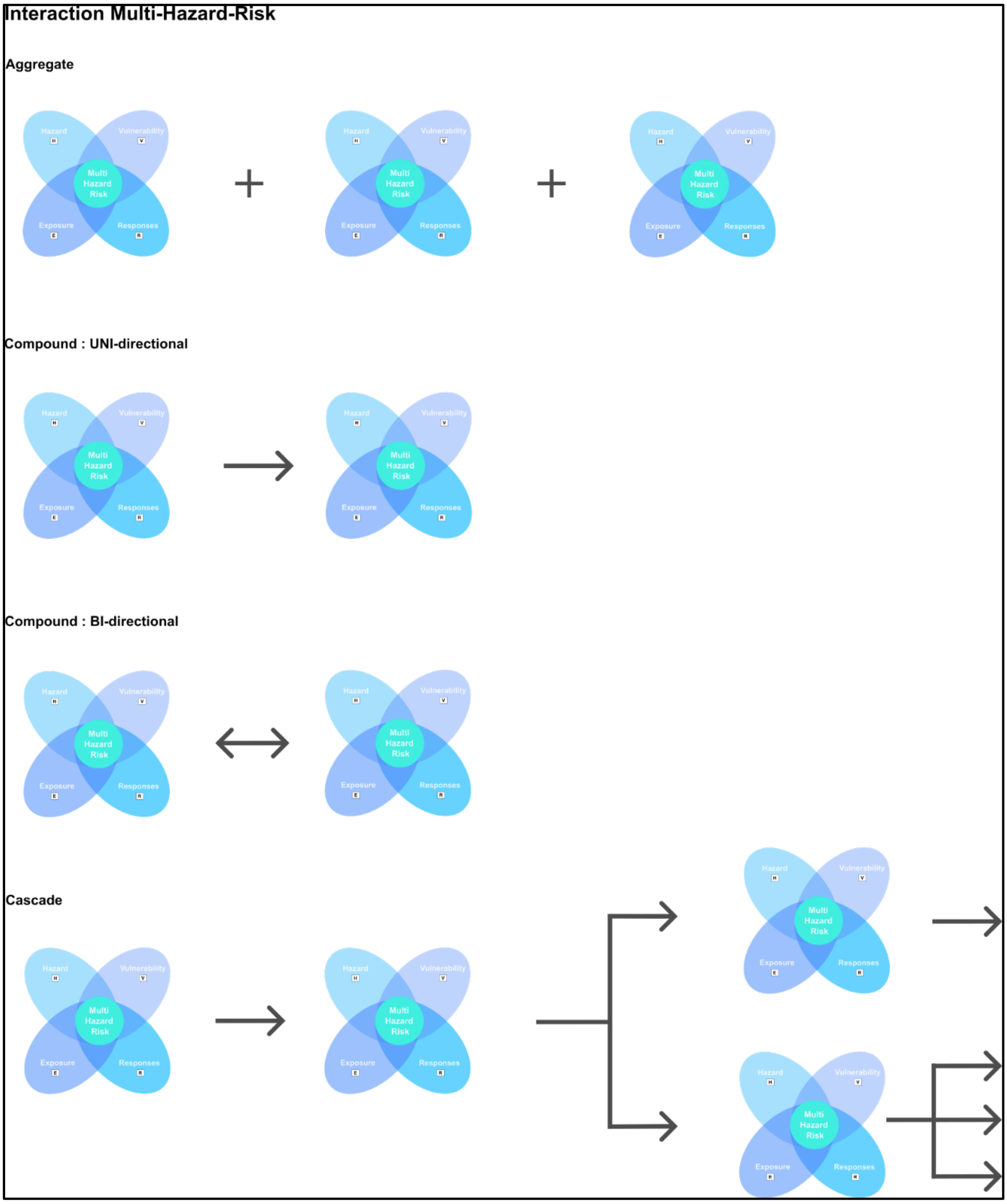

Figure 6: Multi-Hazard-Risk interaction

Knowledge of climate risks is essential for informing climate action aimed at achieving climate-resilient development. Climate actions can accelerate efforts towards developing climate resilience through effective policies, practices, and enabling conditions. In AR6, the term '*enabling conditions*' is used to refer to factors that enhance the feasibility of adaptation and mitigation strategies for climate-resilient development, which is defined as the implementation of mitigation and adaptation measures to foster sustainable development.

Pathways to climate-resilient development are determined by collective social decisions and actions across various spheres including community, socio-cultural, political, ecological, knowledge and technology, and economic and financial domains. Key elements driving high climate resilience development include equity and justice, inclusion, knowledge diversity, and ecosystem management.

In NBRACER, we connect the aforementioned frameworks as a means to directly support Step 2 (risk and resilience assessment) of the P2R journey (Figure 1). A common theme in NBRACER utilizes the "coarse to fine" approach and this idea is applied here. The ISO methodologies (Table 1) offer a framework to then operationalize the risk assessment process (Figure 4) that is needed by WP5 to establish regional baselines and identify resilience challenges across different KCS and communities; the latter identified within WP6. Taken together and expanded, these steps allow the subsequent work of multi-risk analysis (Step 3 in Figure 1) to be undertaken within the resilience journey (Step 3, and beyond, in Figure 1)

In conclusion, a better understanding of the interactions among all risk components is crucial for making informed decisions and creating effective strategies to mitigate and adapt to the changing climate. For this reason, hazard, exposure, vulnerability, risk and response features have been introduced to address the importance of complex risks and their interactions in an integrated manner.

2.2 Introduction to the Scenario Analysis

Scenario analysis is a multifaceted tool that allows investigators to examine how future conditions may look like within a particular system, based on current data and a predefined set of assumptions. It serves to envision how assumptions about systems in the future may be formed. While no model is designed to be perfect, using a framework of scenario analysis can allow urban planners to make informed decisions for management based upon their specific needs.

2.2.1 The baseline scenario

If scenario analysis allows us to investigate assumptions about different future possibilities, it makes sense that a robust understanding of the current, or baseline, scenario is essential. In scenario analysis, the baseline scenario serves as a base of comparison, acting as a metric for change for future assumptions. Although not all the time, baseline scenarios often will use the current snapshot in time, or sometime closely preceding the present day for their reference (e.g. 2020 in Figure 7). This is largely dictated by the "time" that the most complete data "picture" can be painted; data and assumptions here must be analogous to those that will be forecasted in the future scenarios so that a comparison, and subsequent decisions, can be evaluated and made.

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2.2.2 Climate scenarios

Scenario analysis relies on projections of future climate scenarios, (with the "baseline" analysis from above to serve as a comparison) that describe any number of paths that climate change will take in the future, based on collections of assumptions. These assumptions used current data and trends to characterise potential future impacts if those behaviours are continued. The representative concentration pathway (RCP) features 4 scenarios (2.6, 4.5, 6.0, and 8.5 watts per meter squared) that envision different levels of greenhouse gas concentrations as well as different radiative forcing. While socioeconomic factors are not counted in the RCP pathways, the shared socioeconomic pathway (SSP) investigates different levels of policy enactment and societal storylines that would mitigate climate forcing, across 5 pathways (SSP1 through SSP5, respectively, illustrated in Figure 7). For the interested reader, Chen *et al*., (2022) synthesizes many figures comparing the SSP-RCP pathways and the assumptions underlying each respective pathway.

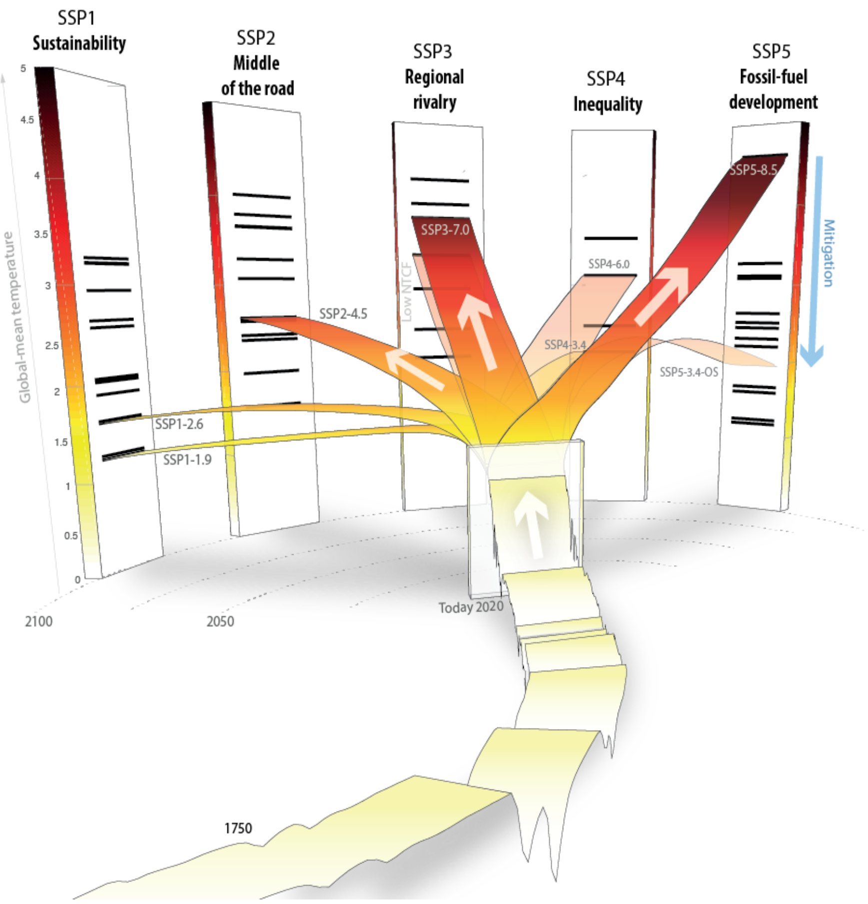

Figure 7: Illustration of the predicted changes in temperature over time under different SSP4 scenarios, which are related to RCP scenarios. The white frame with "Today 2020" represents the baseline in this case (Meinshausen *et al*., 2020).

2.2.3 Integrated Scenario Analysis

With both the baseline and climate scenarios now clear, an integrated scenario analysis combines these scenarios and poses strategic management questions.

Let's examine a brief example, that stacks on the different steps that would involve a simplified "integrated scenario analysis", exploring possible strategies for climate adaptation and mitigation in response to the conditions outlined by the climate scenarios. Say, for example, there is a river that heavily impacts a certain municipality, with an unclear, inconsistent flooding regime. In order to understand this system, we may look at data such as river channel depth, water depth, and average water speed. We also would be justified in looking for precipitation data to examine if there is increased river flooding when it rains a lot. In the course of this, we may also find data that characterizes the river floodplain, or rivershed, soil characteristics and the like. All of these findings would be greatly beneficial in characterizing our river during the current time, as well as serving as a baseline for future comparison.

Carrying this forward, if we were to then take this example and "combine" it with one or more of the RCP scenarios, we may develop a better understanding of how the river may act with increased precipitation. Extending this even further, if we were to use models based around artificial intelligence and machine learning, we could then take these baseline and future scenarios and ask questions like, "what happens if I input an NbS within a section of the river that often floods, will the flooding become less severe?", or even help to identify which areas may experience more flooding in the future.

Although this example is oversimplified, it gets to the core of the potential for integrated scenarios. They can help stakeholders develop and implement different strategies with informed, data-based decisions. While no model or scenario is perfect, the capability to examine a suite of proposed, or even existing climate change measures, can help managers to make informed decisions while decreasing the risk of costly (and sometimes maladaptive) mistakes.

Scenario analysis is not just a "bug" within NBRACER, but a feature. Scenario analysis allows the alignment of social and governance systems within the P2R framework; specifically, Step 6: Adaptation Plan, Step 7: Upscaling/Outscaling, and Step 8: Informed Policy Transformation (Figure 1). Scenario analysis allows stakeholders and decision-makers to make informed, data-based decisions in their evaluations of specific components of their adaptation plans. These plans can be ongoing or those that are being proposed. Scenarios analysis can incorporate social concerns, such as newly proposed restrictions to wastewater effluent limits, or greenhouse gas emissions. Governance models can also be investigated through the economic tariffs, voting structures, or policy transformation and adaptation pathways within the P2R framework (Steps 6-8) in Figure 1.

3. Methodological approaches and models for risk profiling

3.1 Guiding the NBRACER regions in selecting the appropriate risk models

In order to accommodate the differences in regional visions, we propose a data-based approach tailored to each region based upon their unique characteristics. In this approach, the process is guided by the following question, “What are the tools that will guide the regions in selecting the appropriate models”? Regions can take advantage of materials generated from other sections of their work as part of NBRACER and begin applying them to actualize their visions of climate adaptation.

NBRACER WP’s will work alongside regions to incorporate their vision and identify ongoing projects within the case study areas, as well as identify climate change hazards, and biodiversity concerns, and locate the metadata that supply the models of interest. These are performed through tasks and deliverables, incorporated below. Below, we offer a potential walkthrough of appropriate questions to ask or thoughts to consider after placing this workflow in the context of previously completed NBRACER work. In addition to this walkthrough, we offer a decision tree (Figure 10, in the following section, Section 4) to help guide the Regions through the process of determining which model (described fully in Section 4) best serves their needs and visions.

Regional visions were captured by the work performed in WP 1. Specifically, in T1.1 with D1.1, “Report on regional baselines and visions”. This process helped to identify and map stakeholders needed to actualize regional visions, as well as identify pertinent regional climate change hazards, vulnerable KCS, ESS, and NbS that are currently implemented and those applied in the future. After reviewing the regional results from the surveys once more, it may be worthwhile to put the goal into an impactful statement, such as “We’d like to evaluate river flooding risk to two communities that lie within the floodplain of the Special River. We have 1 NbS measure underway and would like to propose 1 restored wetland as an NbS within community 1”

Regions will utilize the conceptual model generated in T5.1 (D5.1). This conceptual model will incorporate the data above in a spatial representation that can be output into models, serving to identify areas for potential NbS implementation. For this exercise, regions would be best served to “break the system down” into its simplest component parts; or as called in the conceptual model, the functional units.

The processes outlined in this section are tied directly to the P2R framework (Figure 1), however, the iterative steps below describe specific parts of the resilience journey that incorporate and eventually expand into other NBRACER WPs. Specifically, we refer to connecting those processes involving mapping capabilities and climate risk (Step 1-Regional Baseline). Subsequent connections include Step 3 (developing solution packages) using multiple modelling strategies for ecosystem services and biodiversity and Step 4 (creating a multi-dimensional portfolio) by combining spatial climate risks with NbS.

3.1.1 Guiding Questions and Thoughts

I need to access the survey to recall our approaches/visions, where is it held?

NBRACER maintains copies of responses should they be needed to coordinate this initial step of selecting the approach.

How do I source regional-level data and what are some general problems often encountered?

Data quality and data availability are chief concerns of the approaches. It is expected that across the Regions, potential sources of data most relevant to the regions have been identified during the questionnaire phases. The questionnaire results, however, may not be exhaustive and it would be beneficial to discuss with regional stakeholders to establish a more complete understanding of capabilities, needs, or otherwise as the questionnaire may have helped highlight missing points.

Why is data quality crucial?

The emphasis on data quality speaks directly to the demands of implementing the models. Their accuracy and success are determined by the quality of the input data. The phase involving data sourcing and quality assurance is often described as the **implementation phase** comprising the following steps: data collection (metadata table), preprocessing, and operationalization (Figure 8).

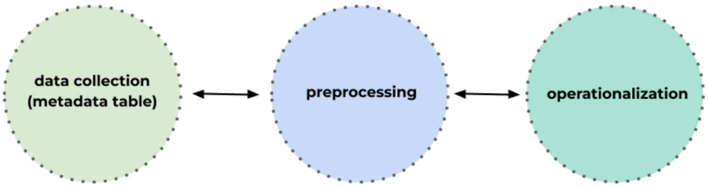

Figure 8: A figure demonstrating the simplified implementation phase of data analysis.

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Data collection constitutes the foundational phase of any data-centric project. This process involves systematically gathering raw data from different sources, such as databases, application programming interfaces (APIs), sensors, social media platforms, or structured surveys. To ensure that the data collected is effectively organized and subsequently utilized, it is imperative to meticulously document the data through the creation of a **metadata table** (an example of a well-structured metadata table is provided in Annex 2). The metadata table serves as a comprehensive schema for the database, providing critical descriptive information that ensures the clarity and usability of the data. This step is essential for ensuring that all stakeholders and team members possess a unified understanding of the dataset. It facilitates thorough data integrity checks, allows for the early identification of potential issues, and serves as a vital reference throughout the entire data lifecycle. Without a well-structured metadata table, managing and leveraging large datasets can become inefficient and prone to errors, compromising the overall quality of the project.

Following data collection, the raw data typically requires substantial refinement before it is suitable for analysis or modelling. The **preprocessing** phase is crucial for cleaning, transforming, and consolidating the data to ensure it meets the standard necessary for subsequent analytical procedures. The key activities required during preprocessing are to identify and rectify errors within the dataset, including handling missing values, removing duplicates, detecting outliers, and normalizing inconsistent formats. Concurrently, this phase encompasses scaling numerical data, encoding categorical variables, and applying feature engineering techniques. Preprocessing is essential as it ensures that the data are clean, consistent, and formatted appropriately for robust analysis. This step is crucial for minimizing the risk of errors and validating analytical results. By transforming raw data into a refined and structured format, preprocessing establishes a reliable foundation for subsequent modelling and analysis.

Operationalization refers to the process of deploying and integrating data-driven models, insights, or algorithms into a production environment, where they are utilized to inform decision-making and operational processes. This phase is crucial as it translates the theoretical and analytical work conducted in earlier stages into actionable tools that drive tangible business outcomes.

After a ML model has been developed and validated, it must be implemented in a production environment where it can process new data and generate real-time predictions. Once the model is deployed, it is essential to continuously monitor its performance to ensure it remains effective and accurate over time. This ongoing oversight helps to maintain the model's relevance and reliability in the face of changing data and conditions.

Operationalization is where the full potential of data science is realized. The effectiveness of insights or models depends significantly on their practical application within decision-making and operational processes. However, it is important to understand that data alone does not provide solutions or answers. Instead, the right questions posed and the methods employed to analyse data in search of potential answers guide the strategic direction. By formulating pertinent questions, innovative solutions and proposals can be developed to address specific needs and challenges.

What is the process to determine the appropriate data quality and quantity needed?

In order to ensure that regions from all technical capacities can perform their own analyses, we have selected three approaches that can be used based upon different considerations of data quality, data sourcing, and computational ability. The three models are:

- Index-based models (e.g., climate risk index)
- Probabilistic models (e.g., Bayesian Networks)
- Machine Learning (ML)/Deep learning (e.g., the Random Forest algorithm)

In this deliverable, a specific model is presented as an example for each of the introduced methodologies: the Climate Risk Index (CRI) for index-based models, the Bayesian Network (BN) for probabilistic models, and the Random Forest (RF) algorithm for ML approaches. These models are well-known and have been extensively tested by NBRACER partners.
The following section outlines the aforementioned methods that can be utilized, based on data availability and quality, incorporating the needs and goals of the regional vision. Each model is addressed after the steps of the implementation phase described above (data collection, preprocessing, operationalization) have been completed. Alongside the brief outline will be publications that serve as a reference to examine the steps and methods more fully.

4. Proposed models for climate risk assessment

The three modelling methodologies were first introduced to the NBRACER Regions on November 19, 2024, during the “Connecting NBRACER Webinar” series. These methodologies have been identified as the most suitable for application within the NBRACER Regions, following a data-driven approach. Following this, key information and requirements for Regions are outlined to effectively implement each model, guiding the necessary resources, data availability, and technical skills needed for successful application. Regions are encouraged to read this section in tandem with the decision tree (Figure 9) that is meant to help guide the selection of the most appropriate modelling approach. The decision tree was co-designed, through an iterative process involving NBRACER collaborators, as well as regional representatives, through a Mentimeter survey, where respondents helped select the criteria forming the decision tree. During this event, stakeholders were divided into breakout sessions within the webinar after being presented with survey questions to ask clarifying questions and concerns not captured through the Mentimeter survey. The questions and their results from the 19 November 2024 webinar are included as an annexe in this deliverable (Annex 1).

It should be noted that the three models presented have a substantial publication history and record of use, as seen within the references of each section. Furthermore, based on their presentation within the Connecting NBRACER webinar series, the regions showed a great interest in the models based upon their active skillsets and regional climate adaptation vision (Annex 1). However, it would be beneficial to place the proposed models within the larger context of risk assessment (Figure 9). We do this as a way to show that there exists a variety of tools, some of which may be implemented currently at the regional level, that can be approached and utilized in tandem, in sequence, or otherwise based upon regional needs.

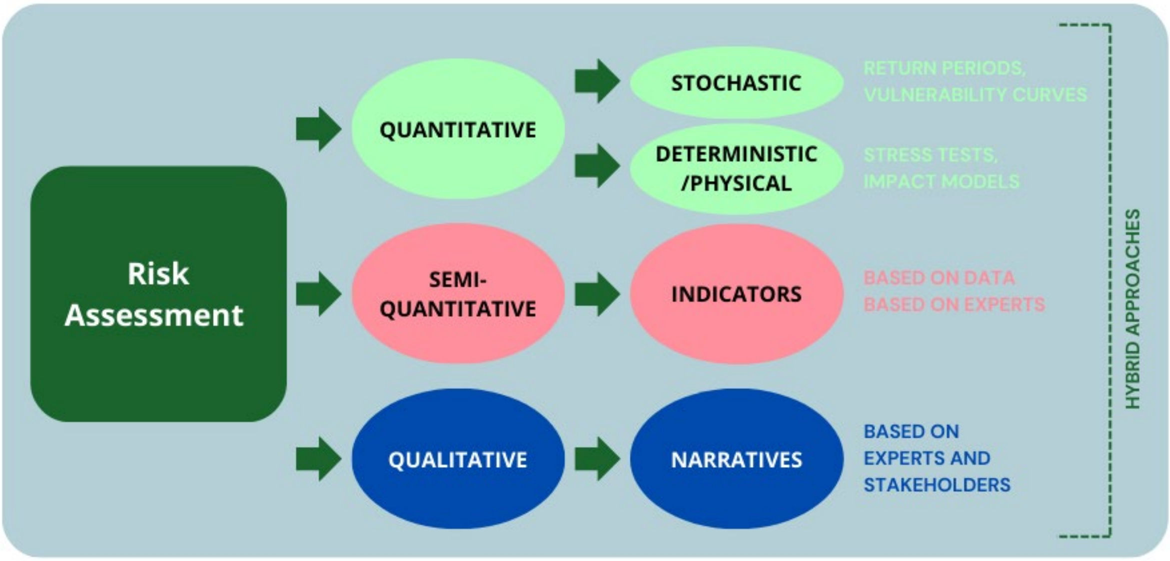

Figure 9: General approaches to risk assessment. Source: Adapted from UNDRR (2022)

More precisely, the index-based model aligns closely with semi-quantitative methods, particularly the use of indicators. This model is effective when working with data of moderate quality or availability and leverages indicator/index-based frameworks to assess risks systematically. It is particularly suited for regional applications where data aggregation and expert judgment play a critical role. The probabilistic model, on the other hand, falls under the quantitative approaches within the stochastic category. This model utilizes statistical techniques, such as return periods and vulnerability curves, to address risks under scenarios of sufficient data quality. It provides robust outputs for understanding uncertainty and variability, especially in climate-related hazards or events. Finally, the ML-based approach bridges quantitative and hybrid methodologies, leveraging advanced computational techniques to derive insights from large and complex datasets. ML excels when high-resolution, high-quality data is available, offering predictive capabilities and a deeper understanding of nonlinear interactions among variables. It also complements deterministic/physical models by refining input-output relationships. More details on each specific modelling approach are reported in the following sub-sections.
By situating these three models within the framework, it becomes evident that they can be applied in tandem or sequentially, depending on the quality and availability of data, as well as

the specific needs and goals of the region. This integrated approach enables the flexibility to adapt tools to the regional context, enhancing the capacity for effective risk assessment and decision-making.

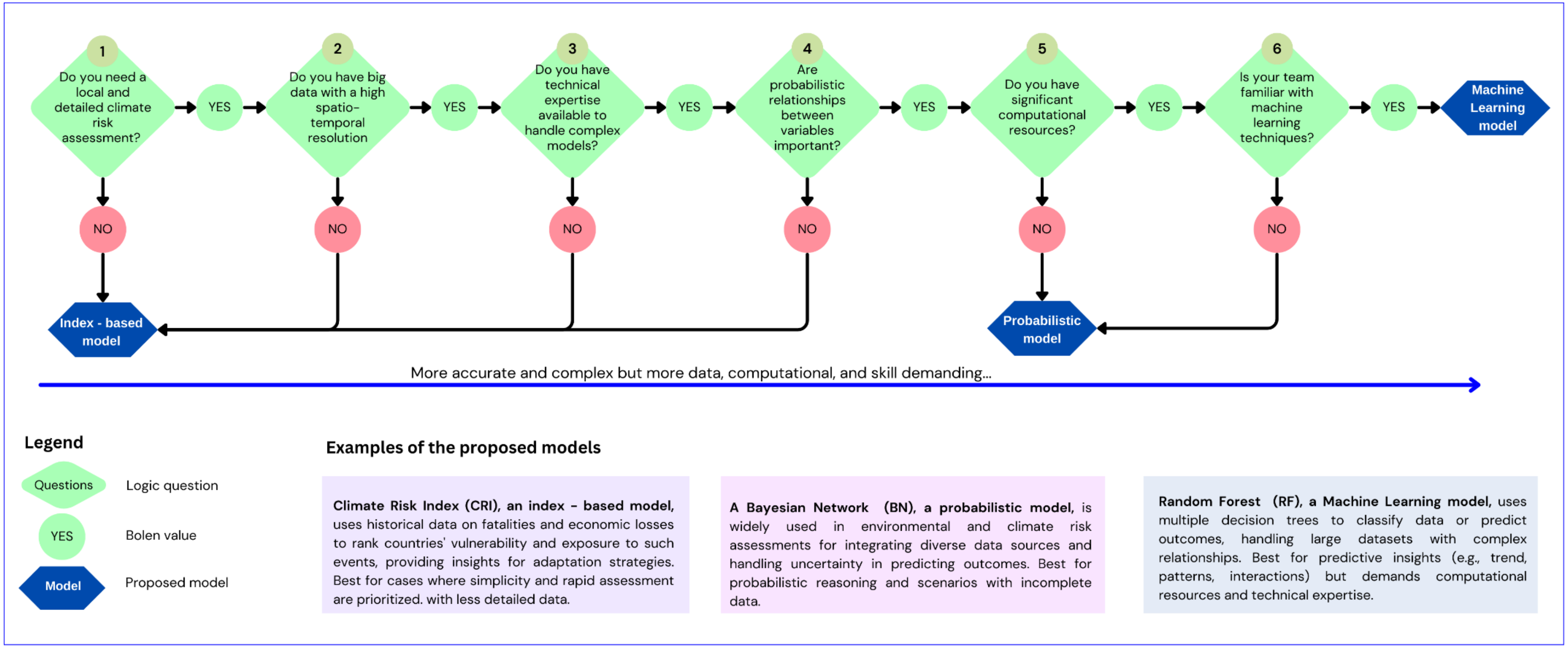

Figure 10: A decision tree comprised of a series of questions to determine if regions would be best served by either an indicators model, Bayesian networks (BN), or machine learning (ML)

4.1 Index-based approaches

4.1.1 Introduction

Index-based models are semi-quantitative methods that use indices to quantify risks, impacts, or phenomena based on measurable variables (Figure 9). These models simplify complex systems by aggregating diverse data into standardized metrics, providing an intuitive way to compare and analyse different scenarios or regions. They are particularly valuable in assessing large-scale environmental or societal issues, where composite indicators can summarize trends and risks effectively. Among various index-based approaches, the **CRI** is a widely recognized tool for evaluating vulnerability and exposure to climate-related risks. In the next sections, this example of index-based methods will be presented, along with the technical implementation steps, their pros and cons.

4.1.2 Climate Risk Index model

The CRI, or indicators model, (Mysiak *et al*., 2018) is a comprehensive tool designed to assess and quantify the risks associated with climate change on a national scale. Developed as a 'first step' for national-level risk assessment, the CRI integrates large-scale data, such as national censuses and European datasets, to provide a broad overview of climate risks. This model, as described by Mysiak *et al*. (2018), is particularly useful for informing national climate adaptation strategies and policies. The index integrates three key components: (i) climate change-amplified hazards, (ii) high-resolution indicators of exposure for selected economic, social, natural, and manufactured capital (MC) assets, and (iii) vulnerability, which includes both current sensitivity to climate-induced hazards and adaptive capacity. The outcomes of the climate risk analysis are utilized to rank subnational administrative and statistical units based on their climate risk challenges. This ranking can also inform the allocation of financial resources for climate adaptation efforts. However, it may not be as effective for local or municipal-level assessments due to its reliance on large-scale data. This is because the methods here rely much on existing data and frameworks present at the national level. Interested Regions would be suggested to research counterpart CRIs and national framework directives in their region of interest.

4.1.3 Implementation steps

General steps for implementation:

1. **Data Collection and Integration**: Gather large-scale national or regional data, including meteorological observations, census data, and other relevant datasets. For example, in China, data from 2288 meteorological stations were used to develop the CRI (Wang *et al*., 2018). We refer interested readers to the preceding publication for examples in "typical" datasets used in this initial step.
2. **Indicator Development**: Develop specific indices to measure various climate risks such as temperature, precipitation, and extreme weather events. These indices should be

statistically robust and reflective of historical climatic conditions (Wang *et al*., 2018; Radovanović *et al*., 2022).

3. **Composite Index Construction**: Combine individual indices into a composite CRI using statistical methods. This step ensures that the CRI provides a comprehensive overview of climate risks (Wang *et al*., 2018; Radovanović et al., 2022)
4. **Risk Analysis and Mapping**: Analyse the CRI to identify areas with high climate risk. This involves mapping the CRI to visualize spatial variations in climate risk across different regions (Mysiak *et al*., 2018).
5. **Policy Formulation and Adaptation Planning**: Use the CRI to inform climate adaptation policies and plans. This includes identifying vulnerable sectors and regions, prioritizing interventions, and allocating financial resources for climate adaptation (Mysiak *et al*., 2018).

4.1.4 Pros and cons

This subsection presents an overview of the key requirements for utilizing the CRI model, along with the types of regions where this methodology is most effectively applied.

Needs from Region to utilise this model: Implementing the CRI involves systematic data collection, indicator development, composite index construction, risk analysis, and policy formulation. As climate risks continue to escalate, the CRI will play an increasingly crucial role in guiding effective climate adaptation efforts. By leveraging the CRI, countries can better understand their climate vulnerabilities and take proactive measures to mitigate the adverse impacts of climate change.

This model is best suited for regions looking for: The CRI is a vital tool for assessing and managing climate risks at the national level. By integrating large-scale data and developing comprehensive indices, the CRI provides valuable insights for climate adaptation planning and policy formulation. Its applications range from national climate adaptation strategies to sector-specific risk assessments and urban vulnerability analysis.
Table 3 summarizes the key advantages and disadvantages of the CRI model, providing a concise overview to help stakeholders evaluate its suitability for their needs.

Table 3: Summary of the main Pros and Cons of a CRI model

Pros	Cons
• Broad, high-level risk overview • Supports policymaking • Easy to use, no advanced skills required	• Limited in local detail • Relies on large-scale, national data • Mostly static, lacks dynamic scenario analysis

4.2 Probabilistic model

4.2.1 Introduction

Probabilistic models rely on mathematical frameworks that incorporate uncertainty and randomness to represent and analyse complex systems. These models are particularly useful when data is incomplete, uncertain, or noisy, as they provide a structured way to infer relationships and make predictions under uncertainty. Probabilistic methods integrate diverse data types and allow for causal reasoning by modelling dependencies between variables. As shown in the framework in Figure 9, probabilistic approaches fall under the **quantitative methods category**. Among these approaches, the **BN** stands out as a robust tool for representing probabilistic relationships in a graphical format, making it ideal for environmental and risk assessment studies.
In the next sections, the BN model, will be presented, together with the technical implementation steps, their pros and cons.

4.2.2 Bayesian Network model

Bayesian Network models, commonly abbreviated as BN, utilize Bayes theorem (Pham *et al.*, 2019) to allow for an increase in model complexity and incorporation of spatial data. BN are statistical approaches built in the form of qualitative structures known as directed acyclic graphs (DAGs) representing the variables of concern as nodes on the graph, with arcs to represent the probabilistic dependencies among variables within the system. Parameterization of the network then encodes marginal and conditional probabilities of the variables (Furlan *et al.*, 2020; Sperotto *et al.*, 2017).

BN have been noted for their ability to integrate heterogeneous data sources, that may include some inputs based on quantitative data, but also some that are classified qualitatively using expert judgement or by incorporating stakeholders' perspectives (Sperotto *et al.*, 2017). These kinds of methods can be designed to tackle complex environmental issues featured by non-linear behaviour and hampered by large uncertainties (Sperotto *et al.*, 2017). Examples utilizing the BN approach have investigated coastal risks in littoral zones and cascading impacts to the anthropogenic and natural systems (Pham *et al.*, 2023) as well as river basin level appraisal of ecosystem services (Pham *et al.*, 2021).

4.2.3 Implementation steps

1. CONCEPTUAL MODEL:
Define the structure of the network and identify its main variables and relationships represented by using a conceptual/influence 'nodes and arrow' diagram (Figure 11), and by applying different learning processes to automatically extract the network structure. As seen in the risk-based conceptual framework, chosen variables can be selected through expert judgement and literature

review (Merz *et al*., 2010; Paprotny *et al*., 2020). The preceding references were incorporated here to serve as an example, but it is important to note that their case is specific (according to their potential influence on the overall flooding risk and as such their likely contribution to the multi-sectoral damages).

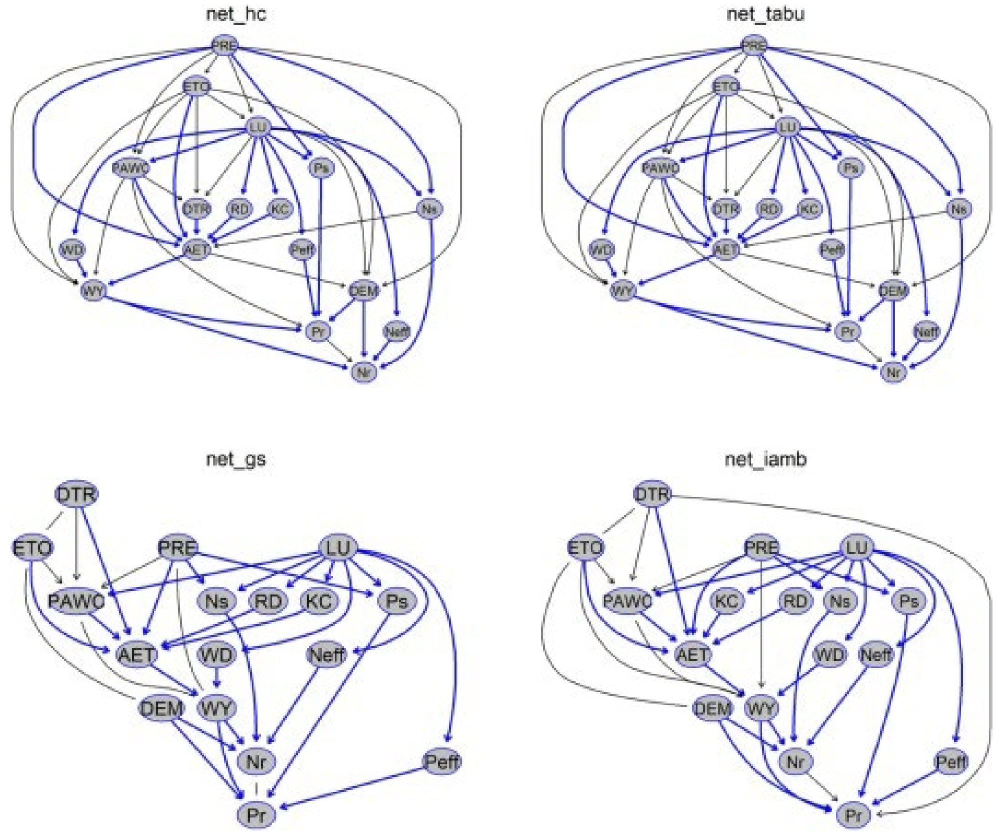

Figure 11: Example of a BN structure from Pham et al., 2021. Arrows indicate the direction of influence from input to response node

Causal relationships are often depicted in a box-and-arrow diagram (as Figure 2, Sperotto *et al*., 2019) that represents the relevant influential relationships; this graphical depiction can be used to define the BN model, incorporating all of the identified variables. The boxes of the diagram are equivalent to the nodes that represent the system variables, with unidirectional arrows between the boxes depicting the arcs that determine the causal relationships between variables in the model, eventually terminating at the assessment endpoints (Sperotto *et al*., 2019).

An alternative approach to understanding the optimal model performance is by analysing various configurations of the model, as defined through expert judgment and pertinent literature. By setting these different configurations and observing the respective model outputs (also in terms of model prediction performance), it is possible to identify which models perform best in comparison to one another (Poelhekke *et al*., 2016). Thus, BN approaches lend themselves well to investigating particular scenarios that stakeholders deem crucial in decision-making along their adaptation journey.

2. MODEL PARAMETERIZATION:

Define states for all variables (interval, Boolean, labelled) and calculate the associated prior probability resulting from data distribution as good relationships between nodes described by the conditional probability distributions. After this input definition is complete, two computations are necessary as part of the parametrization process (Sperotto *et al*., 2019). Firstly, this involves the calculation of the associated prior probability of each state of the node, i.e. the relative likelihood of each possible state without any other knowledge of the variable relationships, based on the distribution of the input data. Secondly, the conditional probabilities of any child node must be calculated as dependent on all possible combinations of the associated parent nodes (Sperotto *et al*., 2017). Finally, a Conditional Probability Table (CPT) is developed to display the relative strengths of the causal relationship between all connected variables.

3. CALIBRATION and VALIDATION:

Evaluating the performance/prediction accuracy of the BN model can be done through two different types of validation methods, namely data-based validation and qualitative evaluation. When performing a data-driven validation, errors in the model output are identified using a statistical test, or in relation to a set of independent observational data. Alternatively, expert judgment can be utilized to perform a qualitative evaluation of the results, or similarly through comparison of the model outputs to those of similar models found in the literature, however this is generally performed when there is insufficient data for statistical testing (Kragt, 2009).

For the estimation of the model predictive error, possible techniques range from Re-substitution and Hold-out methods to the more complicated Bootstrap and Bolstered options (Furlan *et al*., 2020). One such data-based method for evaluating the accuracy of the model is k-fold cross-validation (k-cv), where the data is split into k sets (or folds) of equal size and the model is trained on all but one of these folds, with errors then calculated for the final set of observed data. This process is then repeated with all possible combinations of k-1 folds, and the average error of these different combinations is calculated to reflect the overall accuracy of the model (Yadav & Shukla, 2016).

4. SCENARIOS ANALYSIS:

By inferring the behaviour of the variables at stake against different conditions defined by setting specific state/s of a node/s (evidence) and then propagating information between nodes based on the Bayes theorem, thus resulting in the posterior probability. The next phase of analysis of the BN approach concerns the scenario analysis, in which various potential scenarios are studied in order to predict their respective impacts. The conditions of these scenarios are simulated by 'setting' different evidence for one or more nodes within the BN model, and then propagating that information through the system, thus inferring the behaviour of the variables in order to observe the changes in posterior probability resulting from each scenario (Sperotto *et al*., 2017). In order to infer this information, the direction of propagation must first be determined. A downward propagation of probability is known as prognostic inference, where the values of one or more input (or parent) nodes are set, and the impact on the posterior probabilities of the respective child nodes is observed, usually as far as the endpoints of the BN. Opposingly, the probability of a child node can be set to a fixed value as a form of diagnostic inference, where the change in probability is propagated upwards through the model towards the parent nodes (McNaught & Zagorecki, 2009).

5. SENSITIVITY ANALYSIS:
The relative impacts of each parameter on the output are determined, thus allowing for the identification of the most influential set of variables. The stepwise modification of individual input parameters can then be used to observe changes in the posterior probability. A further phase of analysis identified as mostly absent within the context of the recent literature was a detailed sensitivity analysis. This evaluation should provide information on the sensitivity of the assessment endpoints of the BN model (i.e. damages to the residential, agricultural, and industrial sectors), in relation to changes in their various explanatory nodes.
This analysis can be completed through two phases (Kragt, 2009; Pollino *et al.*, 2007). Firstly, the relative impacts of each parameter on the output are determined, thus allowing for the identification of the most influential set of variables. Further to this, the stepwise modification of individual input parameters can then be used to observe changes in the damage assessment endpoint probabilities. As such, it would also be possible to interpret how the various input nodes impact the model outcome, and understand their relative importance in determining the highest class of flood damages (Furlan *et al.*, 2020)

4.2.4 Pros and cons

This subsection presents an overview of the key requirements for utilizing the BN model, along with the types of regions where this methodology is most effectively applied.

Needs from Region to utilize Bayesian Network models: large dataset that can be used for model training and validation. This can often entail those with significant historical data, provided the records are well maintained.
Bayesian Network models are best suited for regions looking for: continued monitoring and evaluation of already well-studied coastal watersheds or river basins that would benefit from added risk assessment or evaluation of ecosystem services.
Table 4 summarizes the key advantages and disadvantages of the CRI model, providing a concise overview to help stakeholders evaluate its suitability for their needs.

Table 4: Summary of the main Pros and Cons of a BN model

Pros	Cons
• Analyses complex, interconnected factors • Allows scenario simulation • Sensitivity analysis • Integrates qualitative data	• Requires expertise in statistics • Needs diverse data sources • Time-consuming setup and calibration

4.3 Machine learning model

4.3.1 Introduction

Machine learning (ML), or Deep learning, is a subset of Artificial Intelligence (AI) that focuses on the development of algorithms that enable computers to learn from and make decisions based on data. In general, ML is a data-intensive type of model but by utilising different algorithms, heterogeneous data types and quality to be integrated together. Algorithms form the core of ML applications and analyses are tailored to play to the strengths of particular ML algorithm(s) within environmental concerns. Among the wide range of ML algorithms available, one notable example is the RF model, which has been used by some project partners. In literature, this algorithm has been applied solely or en-suite to investigate hosts of environmental, climatic, and hydrological questions. In the next sections, the RF model, one example of the ML methods, will be presented, together with the technical implementation steps, their pros and cons.

4.3.2 Random Forest model

RF has been used to map tropical forest carbon stocks, aiding in the implementation of carbon offset mechanisms such as REDD+ [Reduced Deforestation and Degradation Plus (Schonlau and Zou 2020)]. It has also been employed in weather prediction and climate analyses, where it has shown promise in forecasting extreme weather events and analysing climate change impacts (Schoppa *et al*, 2020). Additionally, RF has been applied in flood discharge simulation, providing a competitive alternative to traditional hydrological models for large-scale hazard assessment (Tyralis *et al.*, 2019). Zennaro et al., utilized RF and multi-layer perceptron (MLP) in tandem to investigate chlorophyll-a concentrations in future climate scenarios at the lagoon scale (2023). This model type is noteworthy as it allows for the integration of expert-based opinion, as seen in Dal Barco *et al.*, (2024).

As the above examples demonstrated, one of the most widely used ML models is the RF algorithm. RF is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees (Tyralis and Papacharalampous, 2017; Scornet et al., 2014).

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This model is known for its high accuracy, robustness to overfitting, and ability to handle large datasets with higher dimensionality. From a computational point of view, RFs are regarded as attractive because they are relatively fast to train and predict (Zhang and Ma, 2012). Secondly, they depend only on a few tuning parameters. Finally, they can be used directly for high-dimensional problems. Moreover, they provide measures of variable importance, differential class weighting, missing value imputation (Zhang and Ma, 2012).

On a more technical note, the RF algorithm is an ensemble predictor that uses a bagging strategy, so deep trees, fitted on bootstrap samples, are combined to produce an output with lower variance. In addition to choosing instances, however, a RF also incorporates random feature sub-spacing techniques (Ho, 1998). When growing each tree, instead of only sampling over the observations in the dataset to generate a bootstrap sample, it also samples over features and keeps only a random subset of them to build the tree. A training sample created using the random subspace method thus contains all the original example instances, each one with the same randomly reduced feature space. Sampling over features has indeed the effect that all trees do not look at the same information to make their decisions and, as a consequence, it reduces the correlation between the different returned outputs. It is another way to achieve the independence of models. Predicting output values for novel instances with an RF predictor involves each individual ensemble member votes for the most probable output according to its learned decision rule (Bianconi, 2021).

According to the reported characteristics and related potentials, a risk assessment modelling procedure can be effectively designed and implemented using the RF algorithm. By integrating data representing each of the main risk components (Section 2.1), an RF-based model can be employed to predict future changes of a specific target (e.g., marine ecosystem) under varying multi-hazard scenarios (e.g., testing the effect of future variation in sea temperature, salinity, etc on the investigated target). This approach supports the identification of hotspot risk areas (e.g., areas where these ecosystems may face risks of disappearance) and therefore such insights can guide the strategic implementation of localized NbS to mitigate risks and foster ecosystem resilience.

4.3.3 Implementation steps

General steps for implementation of an ML model utilising an RF algorithm:

1. **Data Collection and Preprocessing**: Gather and preprocess the data to ensure it is clean and suitable for training. This may involve handling missing values, normalizing features, and splitting the data into training and testing sets (Legasa *et al.*, 2022)
2. **Feature Selection**: Identify the most relevant features for the model. RF inherently provides feature importance scores, which can be used to select the most significant predictors (Rothacher and Strobl, 2024)

3. **Model Initialization**: Initialise the Random Forest model by specifying the number of trees and other hyperparameters such as maximum depth of the trees, minimum samples split, and criterion for splitting (e.g., Gini impurity or entropy for classification) (Scornet *et al.*, 2014)
4. **Training the Model**: Train the RF model using the training dataset. During this phase, multiple decision trees are constructed using different subsets of the data and features, ensuring diversity among the trees (Tyralis and Papacharalampous, 2017)
5. **Model Evaluation**: Evaluate the model's performance using the testing dataset. Common metrics for evaluation include accuracy, precision, recall, F1-score for classification tasks, and mean squared error (MSE) or R-squared for regression tasks (Elavarasan and Vincent, 2021)
6. **Hyperparameter Tuning**: Optimize the model by tuning hyperparameters using techniques such as grid search or random search. This step aims to improve the model's performance by finding the best combination of hyperparameters (Elavarasan and Vincent, 2021)
7. **Prediction and Interpretation**: Use the trained model to make predictions on new data. Interpret the results by analysing feature importance scores and understanding the decision paths of individual trees (Criminisi *et al.*, 2012)

4.3.4 Pros and cons

This subsection presents an overview of the key requirements for utilizing the ML model, along with the types of regions where this methodology is most effectively applied.

Needs from Region to utilize this model: Like BN, data needs here are towards the larger side. This has to do again with model training and validation as well as the increased complexity of the models may reveal more correlated variables to modify or remove.
This model is best suited for regions looking: Expand existing BN models, or those incorporating records/data with depth of coverage across qualitative and quantitative variables. ML can help integrate heterogeneous, multi-source data types but does so with a significant need for pre-processing and technical capacity.
Table 5 summarizes the key advantages and disadvantages of the RF model, providing a concise overview to help stakeholders evaluate its suitability for their needs.

Table 5: Summary of the main Pros and Cons of a RF model

Pros	Cons
• High precision and local detail • Manages complex, high-dimensional data • Adapts to data patterns • Ideal for detailed, site-specific analysis	• Needs extensive, high-quality data • Requires machine learning expertise • Computationally demanding

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5. Tying Scenario analysis together with the proposed models

The crux of scenario analysis lies the informed decisions that are needed to be input into the model, projecting their results into the future. The modelling approaches presented in this deliverable represent a continuum of methods, each with their own strengths, weaknesses, and resolutions, enabling the exploration of scenarios investigating management decisions into the model, as well as the generation of tailored outputs based upon model selection and initial input "decision".

To ensure coherence and alignment, this deliverable is firmly anchored to the conceptual framework outlined in D5.1 (Block A in Figure 3 explicitly references the conceptual framework provided in D5.1). In particular, D5.1 provides the foundations, rationalization, and application of the conceptual models for the implementation of NbS. It offers a structured biophysical foundation that connects climate risks, functional units, and ecosystems, providing a clear methodology to identify and assess how ecosystems contribute to hazard regulation. Incorporating these elements ensures that scenario analyses appropriately capture the capacity of ecosystems, such as wetlands for flood mitigation or forests for erosion control, to regulate hazards effectively.

In this deliverable, the decision tree presented in Figure 10 serves as a guide for selecting the most suitable model for scenario analysis. However, it is essential to ground this selection also in the principles established in D5.1, particularly regarding the implementation of the scenarios analysis, e.g., through of the presence or absence of specific habitats and their role in regulating related hazards.

Regions within the NBRACER consortium may already possess a general schema that they have used to implement their own data-based decision-making protocols. Indeed, there is no singular approach to carrying out this work, but this deliverable can offer support for the three proposed models and provide perspective about what regions need to consider in order to input the right amount of data to have a data-driven, informed decision-making strategy that can ultimately be used to assess strategies of NbS efficiency within their regions.

Looking at the whole process, Figure 3 illustrates how regions can establish a workflow, or project pipeline, utilizing the results of NBRACER tasks and pertinent deliverables. This structured flow ensures that the proposed models are applied effectively, with D5.2 playing a central role within Box 5. However, the success of this stage depends heavily on the foundational outputs from the remaining NBRACER WPs to include the policy, governance, and hazard identification as presented through boxes 1 through 4. In this way, we are also reminded of the overlap in processes (steps 1 and step 2) from within the P2R Framework presented in Figure 1.

More precisely, results stemming from the baseline questionnaire concerning hazards (WP 1, D1.1) alongside concurrent descriptions of governance in the regions (D6.1) were first collected. Then, alongside regions solutions are beginning to take shape and more finely tuned to specific, topical concerns across marine and coastal (D2.1), urban (D3.1), and rural (D4.1) landscape systems.

Finally, extending WP5 outward, the outputs of these scenario analyses provide a robust foundation for subsequent co-creation activities and inform later adaptative management practices, including, but not limited to those activities described in WP 6 and WP7, respectively.

5.1 Considerations for Scenario Building & Implementation Strategies

Most generally, we have assumed that regions will compile their available data en masse, while also including various components related to regional visioning from NBRACER WPs. The end result being (simplified here for context): lists of data, a list of climate risks, NbS projects and various inputs from the social and governance side. All these factors would then need to be assessed alongside each other in order to determine which NbS is suited for a particular case. Thus, a scenario analysis would be informed from across sectors, guided by regional stakeholders to assess NbS management actions.

In contrast to this, we will briefly overview regions and partners that have adopted other approaches. Firstly, we examine the West-Flanders and East-Flanders regions' case study workflow, we will offer, broadly, an outline for their workflow and considerations that are input therein. When looking at strategies (called as *scenarios* in Flanders) for NbS implementation,

The **Flanders region** uses an approach in which climate risks are based on a combination of process based event-models which determine the climate risk. Such models are commonly used by governments and planners for modelling contemporary weather-related risks and management and planning decision-making. When combined with weather events with certain return periods (such as T1000) for future climate scenarios (like RCP8.5), instead of return periods under the current climate, they provide insight into future climate risks. Such current and future climate risks are then evaluated based on their impact on certain indicators, like (but not limited to) the KCS used in the framework of the EU mission for adaptation. Depending on concrete cases and plans, a damage-based approach is used for evaluation, in which for instance flooding of meadows is accepted for events with a shorter return period (e.g. T3 for some areas) than flooding of houses (e.g. T10 000 for some areas).

In the Flanders Region, the portal of the Flemish Environmental Agency[3] uses also scenarios of (nature-based and other) solutions to mitigate climate risk. The scenario-building approach starts from a particular climate risk (e.g. pluvial flooding) that is first selected. Then, for each of the eight scenarios, a policy goal is selected. Scenarios and related policy goals start with the current situation (scenario 0), over the trend (current promised policy, S2), to accelerated trend (S4) and finally a maximal scenario. As an example, a particular policy scenario such as S2 sets a goal of 250m^3 buffer capacity per hectare of sealed land; S7 sets a goal of 330m^3 per hectare of sealed land. Based on potential maps (= maps that show where a set of solutions has the highest potential impact), solutions are then placed over the landscape following the policy for that

[3] https://klimaat.vmm.be/tools/plan

landscape. The results are maps for 8 strategies where NbS are placed in the landscape. Each scenario considers solutions for (pluvial) flooding, drought and heat stress. In the next step, for each scenario, the climate risks (again flooding, drought and heat stress) are again modelled using the process-based event-models described above, with the future climate scenario. This indicates the local and place-based impact on climate risks for each of the eight scenarios. Again, indicators are calculated for this impact.

Furthermore, this process is how the Flanders case study envisions strategy building for assessing the landscape scale impact of NbS, as defined in the NBRACER tasks 2.3, and 3.3, 4.3, across their respective work packages. In their approach, a set of process-based models will be used rather than one integral model. For instance, a separate model on the relationship between plant life cycle and the soil water balance is used for modelling the impact of specific farming NbS, and the results of this model on runoff feed again in a particular event-based runoff/flood model.

Conclusion

Aligned with the flow chart presented in Figure 3 (Section 1.2) and, specifically, Operative Digital Framework (Block B), the goal of this deliverable is to outline technical tools and methodologies that regional stakeholders, cluster leaders and decision-makers could employ to advance integrated scenario analyses able to investigate NbS performance that is aligned with the regional visioning and transformative journey. In particular, WP5's block B supports the entire resilience journey, from risk assessment (Step 2) to informed policy transformation (Step 8). This is performed by utilising a coarse to fine scale approach that NBRACER has deemed the SoS approach and is our guiding principle that integrates social, biophysical, and governance systems. Alongside WP6, the products from WP5 are aligned with the P2R resilience journey and the role of risk assessments (Figure 1).

Risk assessment is a critical component of the P2R resilience journey, enabling a comprehensive understanding of risks that may adversely affect NBRACER regions (a component that is also well described in D5.1 – Section 2, as part of the overall conceptual framework). It provides both qualitative and quantitative estimations of potential risks, focusing on identifying future changes that could impact diverse landscapes (e.g., marine, coastal, urban, and rural contexts) and different KCSs and communities. The primary objective of risk assessment is to guide strategic adaptation planning by identifying major climate threats and framing a clear direction for mitigation and resilience measures. In this deliverable, three methodologies (i.e., index-based, probabilistic, and ML model) have been proposed, together with a decision tree, to support the selection of the most appropriate modelling approach for each region/case study, considering the primary aim, data availability, and computational capabilities and human resources of regional stakeholders. These methodologies are tailored to address the specific needs of the NBRACER regions, ensuring robust and adaptable risk assessment outcomes through a data-driven approach. Moreover, one selected model was proposed for each model type, along with detailed information on technical implementation steps, pros, and cons. These models will be applied in selected case studies of the NBRACER regions with support from NBRACER scientific partners. Finally, this report also highlights the connections and links with other WPs and tasks.

Moving beyond this deliverable through the NBRACER project framework and methodology, we call out the following synergies:

- Coarse to Fine Approach: The flexibility and applicability of this approach take into account regional needs and capabilities. No two regions are expected to undergo the same resilience journey, but by utilizing this approach regions with different capabilities move from coarse to fine in their assessment and scenario-building processes.
- SoS and Governance: We have aimed to explicitly state where direct and indirect relations to WP6 are included and again reiterate the need to assess current governance systems, foster policy coherence, and engage stakeholders in decision-making. We call out links to Step 4 (creating multi-dimensional portfolios) and Step 5 (designing adaptation pathways) in the resilience journey to reiterate where WP5 and WP6 are aligned and how their work is connected to the wider NBRACER consortium operating within the P2R Resilience framework.

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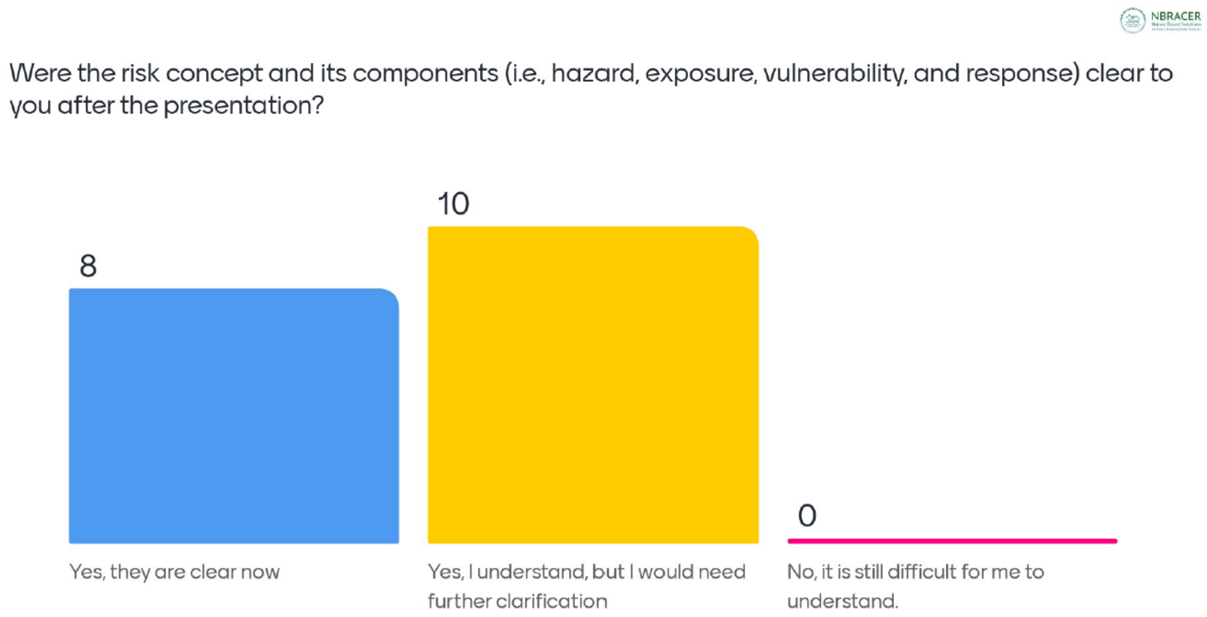
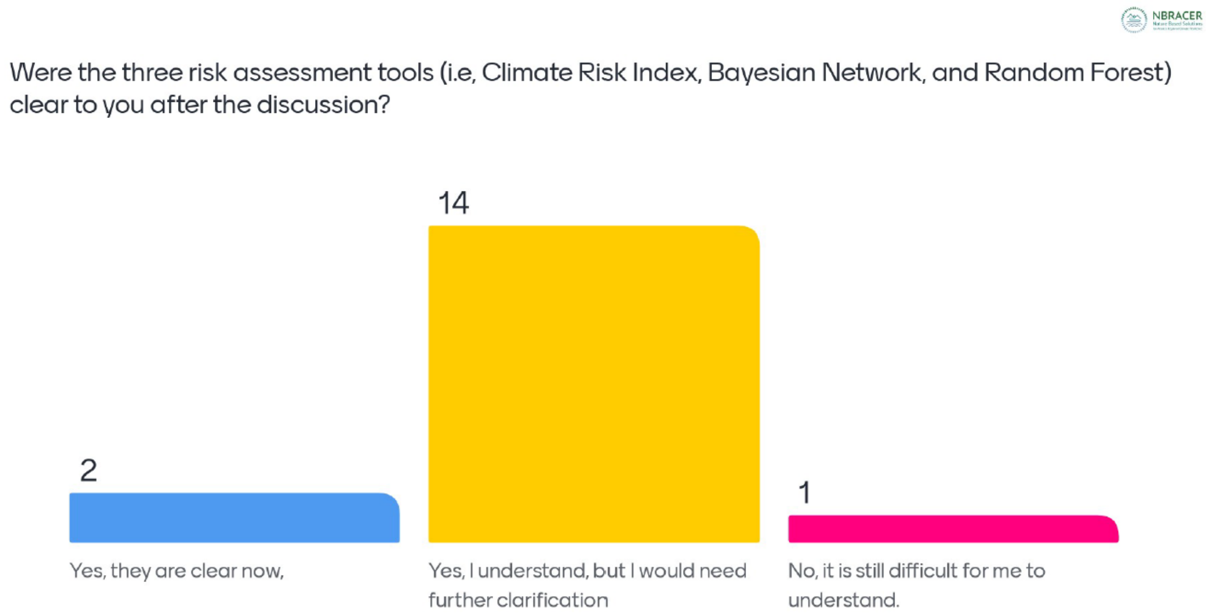
Appendices

Annex 1: Mentimeter questions and results from the 19 November 2024 “Connecting NBRACER Webinar” series poll.





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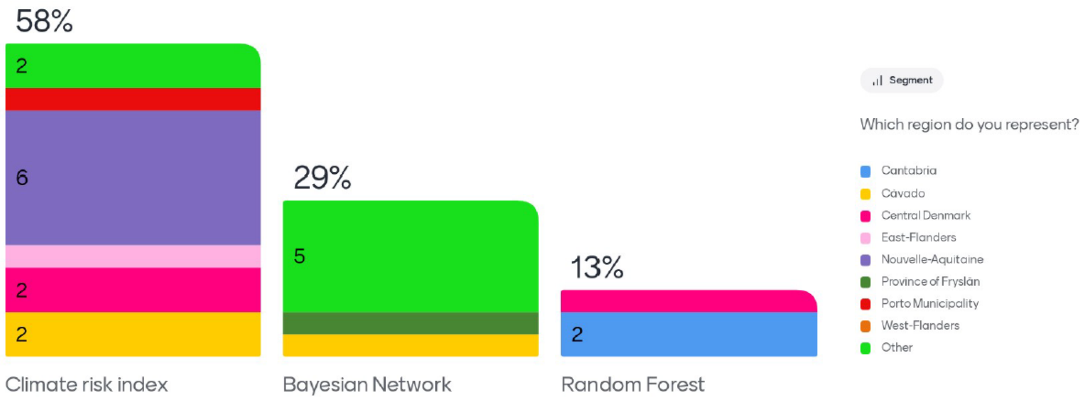
Considering the three tools we have just presented, which one would you find most applicable or beneficial for use in your case study or region?



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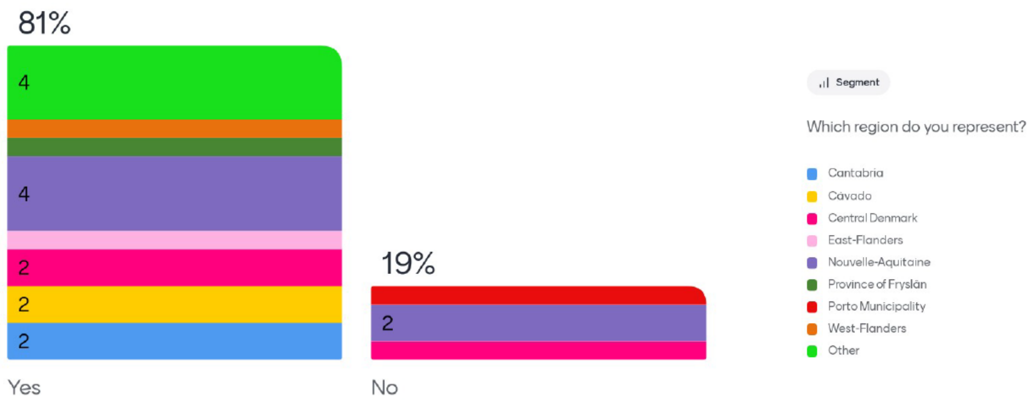
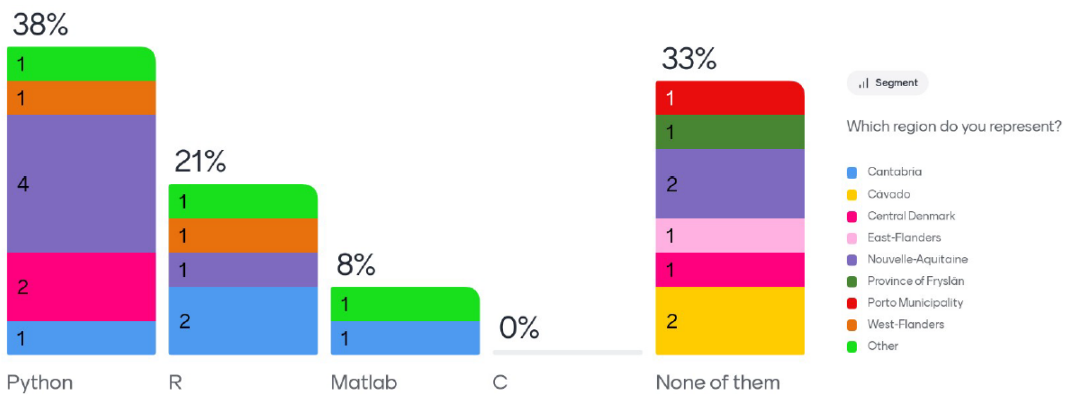
What were the reasons behind your selection of this particular tool? (Please add your region in brackets)

- Some landscapes could be analysed by random forest approach, but I think that Bayesian approach could be applied to the three landscapes
- we have already a model approach, which is physical
- we have already a model approach, which is physical
- Also qualitative aspects included
- Less data hungry model
- Actually I'm not sure if we can respond positively as I don't know if we have the skills to do it
- We have experience in this method and have done other projects fx susceptibility mapping for landslide risk and LULC projects
- Addressing interconnectivity (Deltares)
- Central Region Denmark
- I think the BN fits best as we already have quite some data that would fit into this model and we are interested in further analysing ecosystem services. I think CRI would be also possible.
- Given that CRI methodology was already implemented for the creation of the regional strategy for climate change adaptation.
- I think we have enough data available and people with experience
- "Cávado" is envolved in the 3 landscapes, therefore, the complexity of the problem maybe can be addressed in this methodology
- less data hungry model
- (Nouvelle-Aquitaine) : it identifies regional vulnerabilities to extreme weather (flood risk). Easy and uses GIS tools
- CRI helps identify climate risks, assess interventions, and prioritize resilience actions for WP2 and WP4.
- I use the probabilist approach
- Least data hungry model
- Data-driven model is better for us and let the statistics to show which is the best to predict the risk...
- Let statistics to choos the potential risk drivers!
- We have enough data available and people with GIS/R expertise (Cantabria)
- We are mainly interested in the relation between our NBS and climate risks mitigation (Porto Muni)

Does your team have GIS (Geographic Information Systems) skills?



Does your team have capability in a programming language?



Annex 2: Example of a Metadata table used to support the implementation of a risk assessment procedure.

DETAILS OF REPORTING PEOPLE		Data identification			Technical characteristic							Spatial characteristic		Temporal characteristic		Landscape characteristic		
NBRACER partners	**Reporting people***	**Code**	**Name of dataset**	**Name of variables**	**Unit of measurement**	**Data structure**	**Historical/ forecasts**	**Type of data**	**Format**	**Estimated size**	**Data standards for interoperability**	**Spatial coverage**	**Spatial resolution**	**Temporal coverage**	**Temporal resolution**	**Envir. Domain**	**Envir. Sphere**	**Theme**
XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX