D3.4 – Initial climate V&R assessment

Regions 4Climate

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List of Acronyms

AR	Assessment Report
AST	Adaptation Support Tool
IPCC	Intergovernmental Panel on Climate Change
CDD	Consecutive Dry Days
CLIMAAX	Climate Risk Assessments for every European Region
CRA	Climate Risk Assessment
DG CLIMA	Directorate-General for Climate Action of the European Commission
DRMKC	Disaster Risk Management Knowledge Centre
EEA	European Environment Agency
EUCRA	European Climate Risk Assessment
PCA	Principal Component Analysis
SPAM	Spatial Production Allocation Model
UNDRR	United Nations Office for Disaster Risk Reduction
WASP	Weighted Anomaly of Standardized Precipitation

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Keywords list

- Climate risk assessment
- Hazard, exposure, vulnerability, response, and risk

Disclaimer

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Executive summary

Deliverable 3.4 is part of the Regions4Climate (R4C) project, in fulfilment of the Grant Agreement number 101093873. Its objective is the provision of the Initial Climate Risk Assessment (CRA) that will establish the baseline risk analysis developed in R4C's Task 3.1. The assessment focuses on four key climate risks: coastal flooding affecting the built environment, droughts affecting agricultural activity, heat-related human mortality, and outdoor heat stress on the human population.

By integrating methodologies and frameworks from the IPCC, CLIMAAX, and ESPON CLIMATE, the CRA offers a comprehensive approach to regional risk assessment. The assessment employs a hybrid methodology that combines quantitative and semi-quantitative approaches to evaluate hazard, exposure, vulnerability, adaptation capacity and response. Quantitative methods rely on high-resolution spatial data, climate models, and damage functions to assess physical impacts. Semi-quantitative methods incorporate indicators to measure adaptive capacity and response, reflecting socio-economic, institutional, and governance factors. Adaptive capacity derived using Principal Component Analysis (PCA), and response, calculated through the Regional Resilience Maturity Model, contextualize regional vulnerabilities and recovery potential, enabling a more nuanced understanding of climate risks.

The risk of coastal flooding on built environments is assessed through flood depth-damage curves, Local Climate Zone (LCZ) classifications, and high-resolution flood maps. These methods calculate economic damages to urban areas under different climate scenarios. Within R4C the analysis identifies South Aquitaine as the region with the highest annual damages, exceeding €300 million.

For the risk of droughts on agricultural activity, the assessment employs the WASP index, which evaluates precipitation deficits, combined with spatially explicit indicators of agricultural exposure and vulnerability. Regions such as Troodos and Castilla y León face the highest drought risks, driven by arid conditions and extensive reliance on agriculture. In contrast, cooler and wetter northern regions show significantly lower risks.

The risk of heat-related human mortality is analysed using quantitative data on heat-related mortality, complemented by regional vulnerability indicators. Mortality is projected using epidemiological models and integrated with climatic data to estimate the population at risk. Tuscany and Troodos exhibit the highest heat-related mortality rates.

The risk of outdoor heat stress on human populations is evaluated using the Universal Thermal Climate Index (UTCI), which models thermal stress based on temperature, humidity, and wind speed. LCZ classifications refine the analysis, allowing for localized assessments of urban heat stress. Regions such as Tuscany, South Aquitaine, and Troodos are identified as the most affected, with significant person-hours of extreme heat stress.

This deliverable provides a robust framework for understanding climate risks across European regions, combining advanced modelling techniques with socio-economic analysis. This framework will be part of the project's legacy and will be applicable to other European regions if they so wish. The results reveal substantial variability in risks, driven by both climatic and regional factors, and emphasize the importance of integrating adaptation and mitigation strategies into regional planning. This initial assessment sets the foundation for future analyses, including long-term climate scenarios, and supports harmonized resilience-building efforts across Europe.

1. Introduction

In the last decades, a variety of frameworks have been developed related to climate risks assessments (CRA). Since the IPCC AR5, conceptual concepts and terms have evolved and therefore, risk assessment frameworks. According to the latest scientific developments in CRA field, a proper design of a CRA depends on several factors, such as the recognition of the complex nature of risks and its uncertainties, the use of multidisciplinary approaches for a more holistic CRA, the assessment of exposure and vulnerability dynamics, among others. Currently, these factors are gradually being incorporated into CRA; however, there are still gaps to be filled.

The objective of this deliverable (D3.4), which falls under WP3, is to develop a holistic climate risk assessment in the partner regions of Regions4Climate project to provide valuable information to the partner regions. This CRA is built on the outcomes of the previous deliverable Climate risk assessment framework (D3.1) which is aligned with the project funded under HORIZON-MISS-2021-CLIMA-02-01 (CLIMAAX project). CLIMAAX transfers the state-of-the-art of CRA frameworks into a harmonized framework to support European regions and communities to better understand their climate change related risks. Besides, the R4C framework is complemented with other relevant frameworks (e.g. IPCC AR6, 2022) and UNDRR, 2022) and European projects (ESPON CLIMATE Update, 2022 and PESETA IV, 2020; among others); in this sense, new concepts emerging in the field of CRA are incorporated in the framework in line with the latest developments in this field.

The vulnerability and risk assessment of R4C framework puts risk at the centre of the framework and is understood as the dynamic interaction of climate-related hazards (including hazardous events and trends), vulnerability, exposure, and response. The incorporation of the latter term (i.e. human responses to climate change) into the risk analysis, as well as the dynamic nature when characterizing the exposure and vulnerability of regions, make the framework innovative. On the other hand, its linkage to the D4.1 "Regional Resilience Maturity Model and Framework" as well as to the D2.2. “Just transition framework” through indicators that characterize the response component, makes the regional-scale vulnerability and risk assessment of R4C being holistic and just.

The following deliverable is organized as follows. Section 2 presents the scoping of the CRA including objective, spatial units, spatial coverage, climatic and non-climatic scenarios and the general CRA approach. Section 3 outlines the identification of the key risks to be analysed, as well as the criteria followed in the analysis. Section 4 is the longest section and sets out in detail the methodologies are used to analyse each of the risks and the main results obtained. The last section presents the conclusions that are reached on the basis of the preceding analysis.

2. Scoping

Scoping prepares the ground for the risk assessment, designing aspects such as the objective, scope, scale of analysis, climatic and non-climatic scenarios, the temporal periods, and the methodologies to carried out the risk assessment.

2.1. Objective

The objective of this climate risk assessment, conducted in task 3.1, is to furnish the project partner regions with knowledge about the risks affecting them. This is to be achieved through the utilisation of frameworks, methodologies and data sources that are up-to-date, comparable, and scalable to other regions in Europe. The assessment is expected to be of interest to the regions concerned and to serve as a basis for decision-making. It is also intended to identify possible priority measures of various kinds.

2.2. Spatial units

The spatial units to develop the vulnerability and risk assessment belong to the administrative units. These administrative units correspond with geographical areas for which an administrative authority is empowered to take administrative or strategic decisions. To represent them, the NUTS classification established by Eurostat will be used, which subdivides the economic territory of the Member States. This classification is hierarchical and is divided into three levels: NUTS 1, NUTS 2 and NUTS 3. For this assessment, NUTS3 has been selected, which subdivides the first and second levels. Table 1 shows the administrative units corresponding to each partner region. In the case of Troodos network, there is no division for such level.

Table 1. Administrative units corresponding to the NUTS3 classification for each partner region.

Partner region	NUTS3	Partner region	NUTS3
Basque Country	Provinces	**Uusimaa**	Regions
South Aquitaine	Departments	**Pärnumaa**	Groups of counties
Azores	Groups of municipalities	**Sitia**	Prefectures
Tuscany	Provinces	**Castilla y León**	Provinces
Køge Bay	Municipalities	**Nordic Archipelago**	Regions
Burgas	Oblasts	**Troodos**	-

2.3. Spatial coverage

The study area of the CRA consists of the 12 regions that are part of the project: Basque Country, South Aquitaine, Azores, Tuscany, Køge Bay, Burgas, Uusimaa, Pärnumaa, Sitia, Castile and Leon, Nordic Archipelago and Troodos. The locations of these regions are represented in Figure 1.

Figure 1. Partner regions of R4C.

2.4. Climatic and non-climatic scenarios and temporal reference

Climate change will be assessed by comparing past (1981-2010) and future conditions (2070-2100) under three potential scenarios:

- SSP1- RCP 2.6 (Sustainability) - which is considered a low emissions scenario where emissions start declining beyond 2020. This declining is due to the world shifts gradually toward a more sustainable path.
- SSP2- RCP 4.5 (Middle of the road) - which is a scenario where historical patterns of development are continued throughout the 21^{st} century.
- SSP5- RCP 8.5 (Fossil-Fuelled Development) - which represents a very high emissions scenario where emissions continue to rise throughout the century, as human development will be driven by an energy-intensive, fossil fuel-based economy.

It is worth mentioning that these scenarios will be linked to the qualitative scenarios developed in the R4C project deliverable D2.4 "Just Transition Roadmaps". Those qualitative scenarios will provide the narrative description of the quantitative scenarios analysed in task 3.1.

The climate risk assessment is divided in two deliverables. In the current deliverable, "D3.4 - Initial climate risk assessment", the climate risk for the reference period is assessed. The future climate and non-climate scenarios will be assessed in deliverable "D3.6 - Final climate risk assessment".

2.5. CRA approach

As discussed in deliverable "D3.1 – Climate risk assessment framework", there is a wide variety of CRA frameworks. In general, it can be said that there is a broad consensus on the key elements to carry out a CRA, although there are some differences and particularities among them. The CRA framework proposed in Regions4Climate is based on existing international CRA frameworks considering the particularities of the project and the availability of information in the study areas. Therefore, special consideration has been given to IPCC AR6, UNDRR, CLIMAAX and ESPON CLIMATE Update due to their relevance at the scientific community on CRA and at European level. Figure 2 presents the general structure of the R4C framework. Risk is located at the centre of the framework and is understood as the potential for adverse consequences for human and ecological systems triggered by the interactions of climate-related hazards (including hazardous events and trends) with the vulnerability, exposure of human and natural systems, and responses. Climate change is considered as underlying risk driver in the framework; however, there are other underlying risk drivers altering vulnerabilities and exposure, such as changes in population and land use. The adaptive capacity is commonly considered as part of the vulnerability.

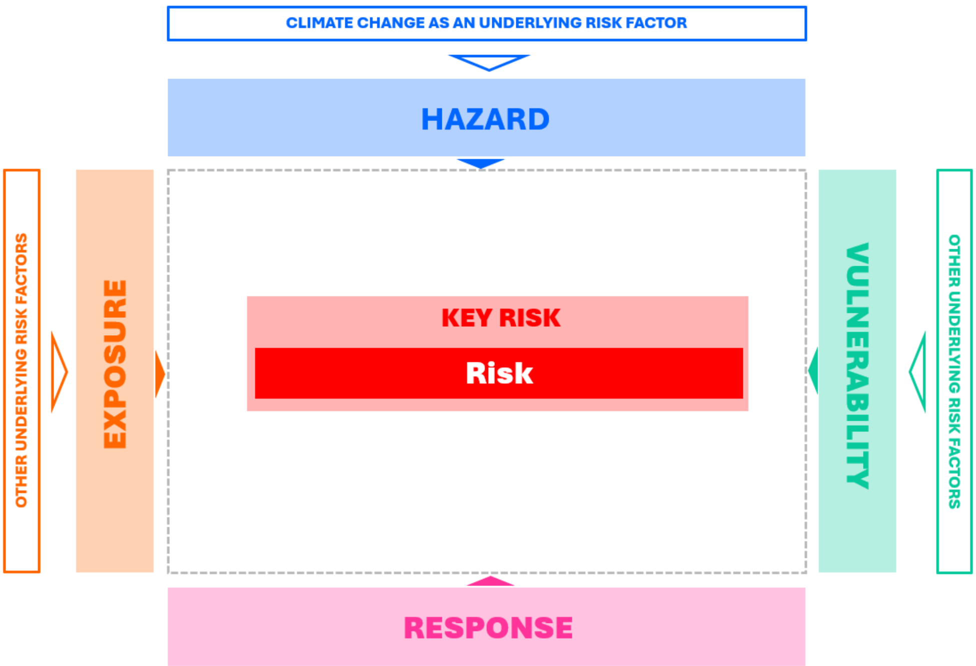

Figure 2. General structure of R4C framework (Adapted from UNDRR, 2022).

The application of the proposed framework requires a variety of methodologies, which are specific to the key risk being analysed. These methodologies are contingent upon several factors, including the state of knowledge regarding specific hazards or their potential adverse consequences on specific receptors; the availability of data; the existence of previous studies; and other factors. To illustrate, there may be certain risks for which the level of knowledge is mature and for which quantitative impact models exist. In contrast, for other, more recently identified risks, or those that are inherently intractable quantitatively, a semi-quantitative or even qualitative approach may be more appropriate.

According to UNDRR (2022), methodologies can be divided into:

- **Qualitative**: this approach is used when the knowledge of risk is limited or there is slight information available. It is based on expert judgement or can be built on qualitative research techniques, such as structure interviews or focal groups. This methodology is easier to apply and does not require a high level of specialisation. Results are not spatially explicit (mappable).

- **Semi-quantitative**: the methodology addresses risks for which quantitative impact models are not available. It is based on the use of indicators to quantify risk and its components. Indicators are derived from available data sources or from expert judgement and they are aggregated through different techniques, such as arithmetic or geometric means (GIZ, 2017). The knowledge to apply this approach depends on the level of detail to be achieved. Results are usually spatially explicit (mappable).

- **Quantitative**: the methodology involves mathematical models (biophysical impact modelling, socioeconomic impact modelling, among others), that require a medium-high level of knowledge. It provides quantitative estimates with respect to a given metric. These estimates are more accurate and are usually spatially explicit (mappable).

- **Hybrid**: it combines approaches, such as the use of mathematical models (quantitative) with indicators (semi-quantitative). It involves a greater effort in terms of knowledge, information, and resources, as more than one technique has to be applied. Results are usually spatially explicit (mappable).

The hybrid methodological approach is chosen for developing the described framework in R4C. This approach allows analysing complex risks in a comprehensive manner obtaining the benefits of the quantitative and semi-quantitative approaches. The quantitative approach will be used to assess the selected potential impacts of regions. This approach is normally based on impact models, which are specific to the type of risk, and resulting results are measurable (e.g. number of dead people, damage to buildings or economic losses). An example could be the use of flood-depth damage curves, which relate water flood depth with percentage of damage to buildings.

On the other hand, the semi-quantitative approach will be applied for assessing the adaptive capacity, as part of vulnerability component, of regions and the response component. The semi-quantitative approach involves a selection of proxy indicators. According to (GIZ, 2017) a good indicator follow the following characteristics: (i) it is reliable, valid and represent adequately the component of risk that is assessing; (ii) it has a precise meaning, and its direction is clear; (iii) it comes from a freely available dataset. Adaptive capacity will be calculated based on ESPON CLIMATE Update but including additional regions since Azores was not considered in that project originally. On the other hand, response will be calculated based on the Resilience Maturity Model from Regions4Climate's WP4.

Finally, both the quantitative and semi-quantitative will be combined, i.e. hybrid approach, to obtain the final risk.

3. Risk identification

Once the context and set-up have been defined in the scope phase, risks will be identified. Risk identification phase is about identifying the risks that will be considered in the risk analysis. In this project, this selection builds on several criteria (i.e. assessment of region needs for CRA, alignment with R4C societal challenges, alignment with CLIMAAX project and data needs). Firstly, it is ensured that the selected hazards and sectors are a necessity for the regions and meet the societal challenges of the project. Then, it is verified that the methodology for impact assessment is available in CLIMAAX. Finally, the data needs criterion adjusts the final selection of the key risks. A description of each criterion is given below:

- **Alignment with R4C societal challenges**. The regions in R4C project are grouped in three different clusters which shares common challenges. The first cluster identified sea level rise, coastal erosion, storm surge and ocean warming as common hazards. The second cluster highlighted extreme storm events, flooding, higher temperatures, and droughts. Finally, the third one identified heat waves, water scarcity, rural depopulation, and pressure on agriculture as challenges.

- **Assessment of region needs for CRA**: this criterion is built on the conclusions of the gap analysis report developed in WP3, which contributes to a revision of the state of the question in relation to the risk assessment in the R4C regions (Annex 1). According to this, the needs of regions in selecting key risks for in-depth analysis are relatively similar. In general, heat stress, drought and coastal flood are the three most prioritized hazards.

  Regarding sectors, agriculture sector raises the biggest concern when studying the drought hazard, while a set of sectors are prioritized for coastal floodings (i.e., built environment, population, biodiversity and commerce and services sectors) and heat stress (i.e., population, social services, agriculture, forestry, biodiversity and built environment).

- **Alignment with CLIMAAX project**: this criterion refers to the selection of the risks based on the workflows elaborated in CLIMAAX. CLIMAAX has developed several risk workflows based on state-of-the-art literature and latest scientific development to support European regions in their climate risk assessments. These risk workflows, entitled as floods, drought, exposed drought population, wildfire, storm, blizzard, and snowfall, describe risks and its components following a harmonized framework.

- **Data needs**: the needs for risk assessment revolve around the availability of hazard data for historical and future scenarios, as well as the availability of information to characterize exposure, vulnerability, and response. Thus, the final selection of key risks will depend on the availability of information (i.e., high resolution data in raster or vector format) at NUT3 for the study area.

Based on the previous criteria, Table 2 presents a preliminary identification of key risks.

Table 2. Key risks analysed with each corresponding acronym.

Key risk	Acronym
Risk of coastal flood on built environment	CF_BE
Risk of drought on agriculture activity	DR_AA
Risk of heat-related mortality	HE_MO
Risk of outdoor heat stress on human population	HS_PO

4. Risk analysis

The section commences with an exposition of the methodological approach and the values obtained for the characterisation of the adaptive capacity and response components. These two components are common to all the risks analysed and are therefore presented initially before a detailed examination of each of the key risks. Thereafter, the methodology and results are described for each of the key risks, which have their specific approaches that are later complemented with the adaptive capacity and response.

4.1. Adaptive capacity

4.1.1. Methodology of adaptive capacity

In this study, the methodology and the selection of indicators for the assessment of adaptive capacity correspond to the ones used in the ESPON CLIMATE Update (ESPON, 2022). In the original project Azores was not included due to the lack of information mainly regarding hazard data. In Regions4Climate, the same methodology to calculate adaptive capacity was applied but including Azores, Madeira, and Canary Islands. This makes it possible to include the Azores, which had not previously been considered, and to obtain an adaptive capacity value that allows us to know where it ranks in relation to all the 1390 NUTS-3 regions studied.

The indicators are presented in Table 3 and the methodology involves the use of Principal Component Analysis (PCA) for the aggregation of indicators. PCA is a dimensionality reduction method that transforms a set of variables into a smaller ones, named components, preserving as much information as possible, and it has already been applied in many studies related to vulnerability assessment (Cutter et al., 2003; Fekete, 2009; Tapia et al., 2017; Navarro et al., 2023). Some of the indicators from D2.1 “Social & economic vulnerabilities analysis” are aligned with ESPON CLIMATE Update.

Table 3. Selection of indicators to characterize the component of adaptive capacity.

Type of indicator	Selected indicators
Technological capacity	Research staff
	Patent applications
	Research and development investments
Social capacity	Investments in education
	Persons with tertiary education

	Risk perception
	Social capital
	Gender equality index
Economic capacity	Employment rate
	Risk of poverty
	Regional GDP
	National GDP
Infrastructural capacity	Medical doctors
	Hospital beds
	Settlement compactness
Institutional capacity	National adaptation strategies
	Regional quality of government index
	Municipalities signatories to the Covenant of Majors

The reason for the inclusion of these indicators is due to the following:

- Within technological capacity, a high level of education and research through tertiary educational attainment, research and development expenditure, and personnel, researchers and patent applications indicate a higher capacity to produce knowledge and develop innovative solutions to new problems (Brooks et al., 2005; Zhang et al., 2018; Medina et al., 2020).
- Social capacity is also relevant. Risk perception is a sociocultural phenomenon affected by social organisation and values, which guides the behaviour of people in prevention and response actions related to hazards; generally speaking, the higher the risk perception the lower the vulnerability (Douglas & Wildavsky, 1982; Grothmann & Reusswig, 2006; Oliver-Smith, 1996; Wachinger et al., 2013; Birkholz et al., 2014; Martins & Nunes, 2020; Medina et al., 2020; Wu, 2021).
- Social capital captures the level of cohesion, trust and access to resources based on social networks; the higher the social capital is, the lower the vulnerability (Pelling, 1998; Wisner, 2003; Nakagawa & Shaw, 2004; Newman & Dale, 2005; Murphy, 2007; Myers et al., 2008; Morrow, 2008; Varda et al., 2009; Ainuddin & Routray, 2012).
- The impacts of disasters are not evenly distributed in society; when there is a high level of inequality among social groups, the impacts are higher. It is also true in the case of gender inequality, which has been captured

with the gender equality index (Bashier Abbas & K. Routray, 2014; Jamshed et al., 2020; Martins & Nunes, 2020; Medina et al., 2020).

- The economic capacity of a territory has a strong influence on the number of resources that may be mobilised to implement mitigation actions and to facilitate the recovery process after a hazard (Cutter et al., 2003; Brooks et al., 2005; Myers et al., 2008; Zhang et al., 2018; Rufat et al., 2019).

- The health system is also an important indicator of the capacity to respond to a hazardous event; in this case, indicators referring to the number of hospital beds and practising physicians are considered (Cutter et al., 2003; Myers et al., 2008; Fekete, 2009; Finch et al., 2010; Yoon, 2012; Chen et al., 2013; Zhang et al., 2018; Maletta & Mendicino, 2020).

- Governance dimension is also an important aspect of the adaptive capacity, which influences the effectiveness of the implementation of disaster risk reduction policies. This is included in the assessment through the quality of government index and the percentage of municipalities signatories to the Covenant of Mayors (Brooks et al., 2005; Kotzee & Reyers, 2016; Medina et al., 2020).

4.1.2. Results of adaptive capacity

PCA has been performed to extract the factors that are able to explain the most variance in the data. Firstly, a series of tests were performed, specifically the Bartlett's test of sphericity was significant at an alpha level of 0.05 and the overall Kaiser-Meyer-Olkin factor adequacy was 0.838. Both tests indicated that the PCA analysis was pertinent.

The selection of the number of factors was based on the elbow criterion, i.e. the interpretation of the factor vs. percentage of variance graph to determine the smallest number of factors that explain the highest percentage of cumulative variance. This resulted in the selection of 4 factors, that explain 70% of the variance. The interpretation of the factors is equivalent to the one from the original project:

- Social and institutional development – This factor is highly correlated with social capacity and institutional capacity indicators like gender equality, social capital, national GDP, investment in education, quality of government, national adaptation strategies and risk perception.
- Hospital resources – This factor mainly explains the indicator hospital beds.
- Innovation – The innovation factor is highly correlated with infrastructure and technological capacity indicators like research staff, investment in research, number of patents, medical doctors and local GDP.
- Economic development – The last factor is highly correlated with economic capacity indicators like employment rate and lack of risk of poverty.

Finally, the factors obtained have been aggregated to calculate adaptive capacity. The adaptive capacity is in the range from 1 to 2, where 2 means very high adaptive capacity, and 1 very low adaptive capacity. Regardless of the other components, the higher the adaptive capacity, the lower the risk.

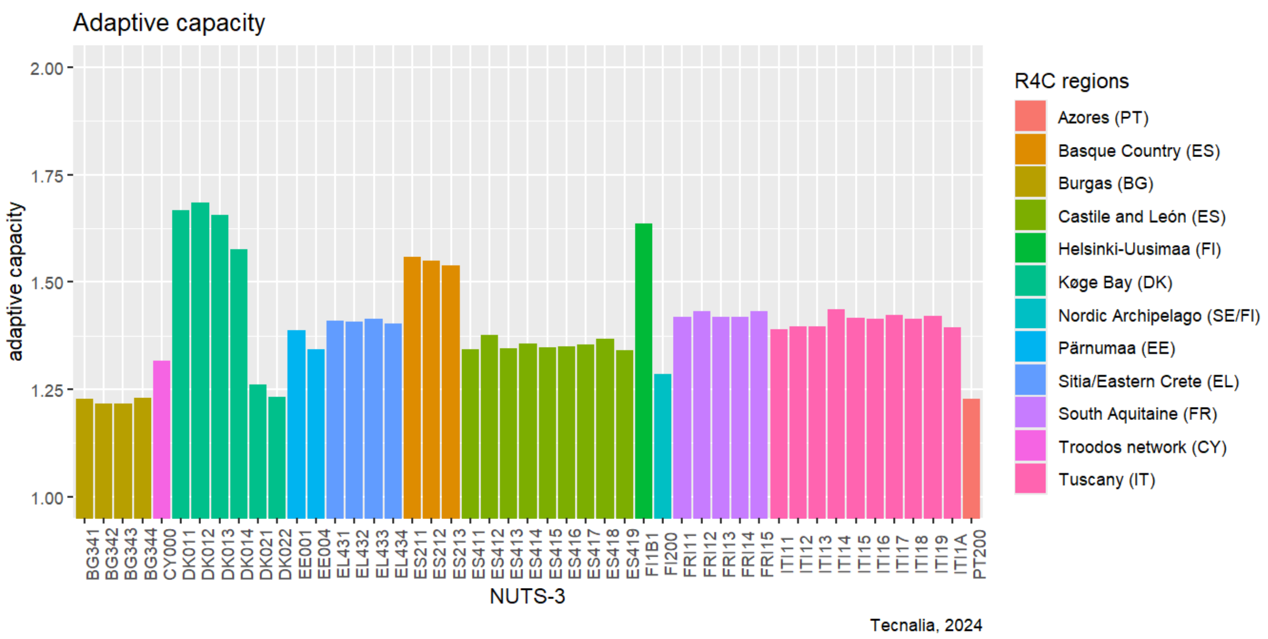

Figure 3. Adaptive capacity of the regions in R4C.

The Figure 3 illustrates the findings pertaining to the adaptive capacity. The highest adaptive capacity is observed in the NUTS-3 located in the Helsinki-Uusimaa, Koge Bay, and Basque Country regions. In contrast, the lowest adaptive capacity is observed in the Burgas, Azores, Koge Bay, Nordic Archipelago, and Troodos regions. It is notable that the Koge Bay region contains NUTS-3 regions with a considerable range of adaptive capacity.

4.2. Response

4.2.1. Methodology of response

Regarding the response component, the selected indicators are based on the D4.1 "Regional Resilience Maturity Model and Framework" indicators (Table 4), which are linked to the D2.1 “Social & economic vulnerabilities analysis” and D2.2. “Just transition framework” as they have informed the indicator selection of D4.1. In this sense, just transition will be included in the framework and the fulfilment of the proposed actions in the roadmap will be reflected in the response component and thus, in the risk analysis.

Table 4. List of indicators of the Regional Resilience Maturity Model and Framework.

Dimensions	Indicators
1. Regional Governance and Institutional capacity	1.1 Political support for a just transition to climate resilience 1.2 Regional governance structures for cross-sectoral coordination 1.3 Governance structures for multi-level (vertical) coordination 1.4 Governance structures for cross-border cooperation (across administrative boundaries) 1.5 Engagement in networks 1.6 Anticipatory governance 1.7 Region's monitoring and evaluation system
2. Plans and policy instruments	2.1 Regional plan or strategy for climate resilience 2.2 Integration of planning and regulatory framework for climate resilience 2.3 Policy instruments supporting regional resilience-building. 2.4 Mainstreaming of climate resilience into other regional sectoral plans and strategies 2.5 Regional plan or strategy for emergency response. 2.6 Alignment of existing policy instruments with regional ambitions for a socially just transition to climate resilience. 2.7 Assessment of region's progress towards relevant SDGs. 2.8 Identification of local/regional targets that align with macro-regional S3/S4+ strategies
3. Human resources and technical skills	3.1 Staff assigned to the planning and implementation of climate change resilience actions 3.2 Flexibility in staff contracting and allocation 3.3 Staff's competencies, knowledge and skills to understand and use climate change data and information 3.4 Staff's competencies, knowledge and skills to design and conduct effective participatory and stakeholder engagement processes 3.5 Staff's competencies, knowledge and skills to successfully implement the planned climate resilience and adaptation strategies and measures 3.6 Staff's competencies, knowledge and skills to successfully engage in climate change mainstreaming

	3.7 Staff's capacity building 3.8 Staff's competencies, knowledge, and skills to make use of multiple financing opportunities
4. Participatory governance and stakeholder engagement	4.1 Identification of purpose and clear objectives for stakeholder engagement 4.2 Identification of opportunities and challenges for stakeholder engagement 4.3 Mapping of stakeholders 4.4 Identification of stakeholders most affected by climate change 4.5 Development of a stakeholder engagement plan 4.6 Participatory governance to enhance coordination and agenda-setting 4.7 Engagement with the private sector 31 4.8 Engagement with citizens 4.9 Engagement with organised civil society 4.10 Engagement with academia and research community
5. Public support, awareness and climate change communication	5.1 Climate risk communication strategies 5.2 Dissemination of scientific information and good adaptation practices 5.3 Alignment of regional communication and marketing strategies with climate resilience priorities 5.4 Analysis of public perception of climate change 5.5 Analysis of public perception and acceptance of policies
6. Financial capabilities	6.1 Financial resources availability 6.2 Budget allocation and distribution at local level 6.3 Budget allocation for planning 6.4 Budget allocation for implementation 6.5 Incentives for private sector
7. Vulnerability and Risk Assessment	7.1 Ability to conduct risk and vulnerability assessments 7.2 Risk assessments 7.3 Integrated vulnerability and risk assessments 7.4 Alignment of vulnerability and risk assessments with justice and equity principles 7.5 Comprehensiveness of indicators 7.6 Use of vulnerability and risk assessments' results

8. Innovation Potential Assessment	8.1 Framework conditions - Education & Lifelong learning 8.2 Framework conditions - Research System 8.3 Framework conditions - Digitalisation 8.4 Public investments in innovation 8.5 Innovation activities in SME 55 8.6 Collaboration 8.7 Economic impact of innovation 8.8 Environmental sustainability

4.2.2. Results of response

The response component is calculated from data collected by ICLEI and Zabala in Regions4Climate WP4. In WP4, they have developed a self-assessment tool in which regions can input information related to the indicators in the aforementioned table. From this information, a composite response indicator has been constructed by averaging the indicators per dimension and then averaging the dimensions, and finally scaling the indicator considering the minimum and maximum possible value.

The results of the response component for each of the regions are presented in the following figure. It can be observed that the Basque Country, Burgas, Sitia/Eastern Crete, Koge Bay and Helsinki-Uusimaa regions exhibit the highest response levels. Conversely, the regions with the lowest response values are Troodos and Pärnumaa. It can be stated that even in those regions with high values, there is potential for further enhancement of the response component.

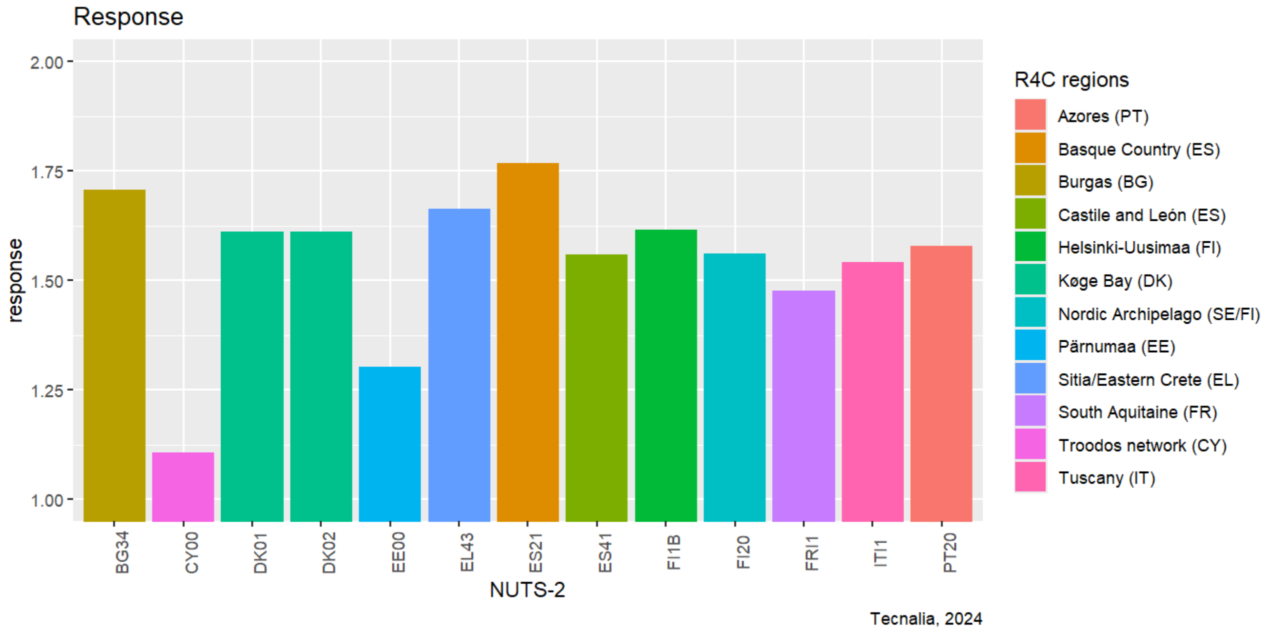

Figure 4. Response component of the regions in R4C.

The response component will be updated by the regions during the project. Therefore, the last updated response data will be included in the final risk assessment.

4.3. Risk of coastal flood on built environment

This key risk is evaluated through a hybrid methodology that combines quantitative and qualitative approaches. The quantitative aspect focuses on assessing the impacts of coastal floods on urban environments using a systematic data-processing workflow inspired by the CLIMAAX project. This step-by-step methodology aims to calculate flood-related damages to the built environment, utilizing datasets summarized in Table 5. To estimate flood damage, depth-damage curves are employed, specifically those from the globally consistent database available at the Joint Research Centre (JRC).

Table 5. Datasets to quantify the impact of coastal flood on built environment.

Potential datasets to be used in the impact analysis	
Coastal inundation	Global inundation maps of flood depth are available from the Microsoft Planetary Computer produced by Deltares.
Local Climate Zones	The Local Climate Zones map is available from the Global map of Local Climate Zones.
Land-use information	The land cover map is available from the Copernicus Land Monitoring Service for the region of Azores.

On the other hand, the adaptive capacity and response components are assessed following a semi-quantitative approach as described in sections 4.1 and 4.2.

4.3.1. Methodology of risk of coastal flood on built environment

Coastal flooding occurs when extreme sea water levels rise during sea storms, exacerbated by sea level rise. The impacts are assessed by analysing extreme water levels at the coast, creating flood maps for events with varying return periods, and conducting impact analyses on these maps to evaluate the resulting damages to infrastructure. This damage assessment integrates maps of potential flood extent with economic damage functions specific to infrastructure. Flood damage is calculated by applying damage curves to inundation depth maps while considering local factors through a Local Climate Zones (LCZ) classification. For each pixel, the calculation incorporates flood depth, LCZ, damage curves, and country-specific parameters approximating the economic value of different land-use types.

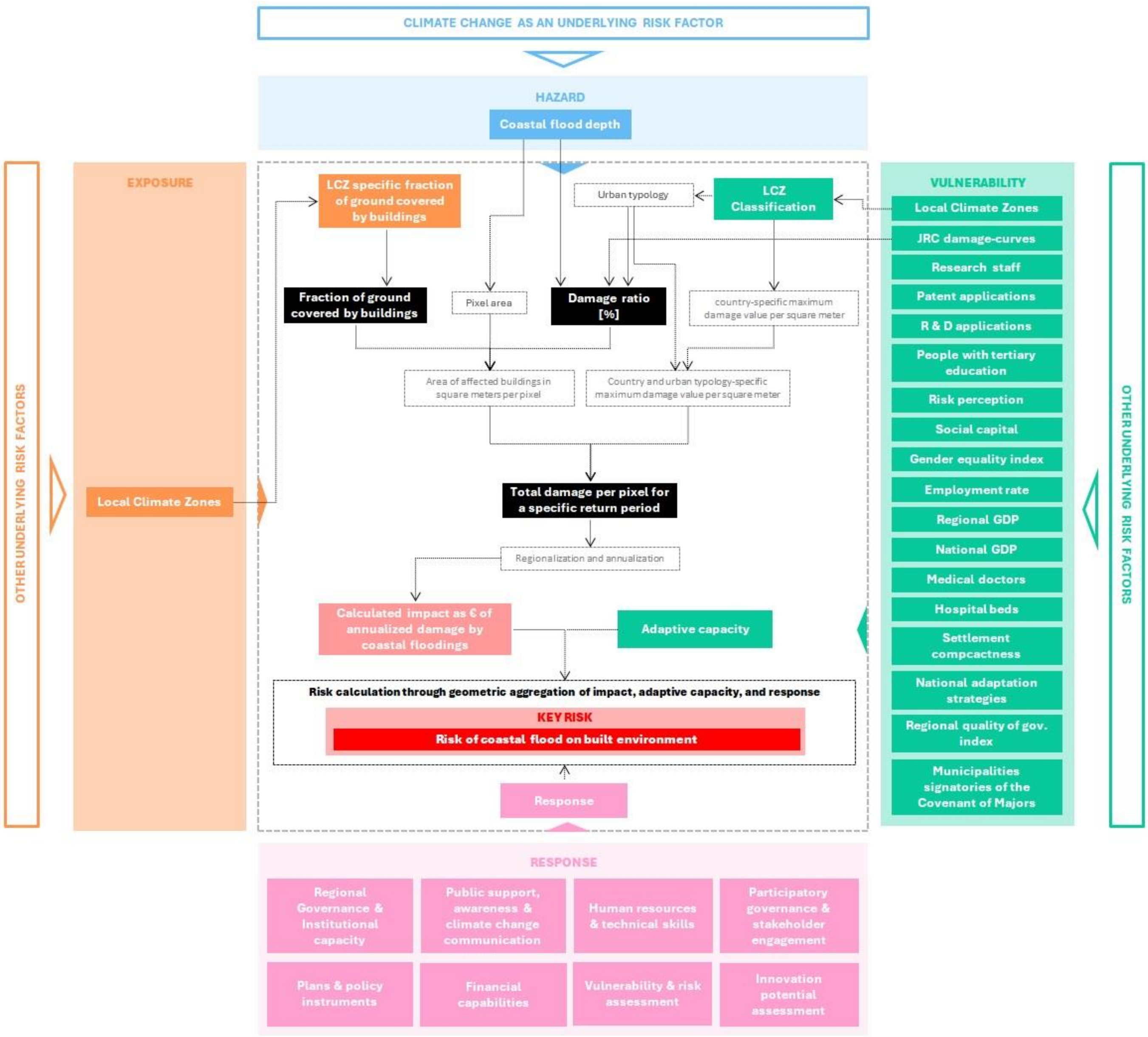

Figure 5. Methodological diagram of the risk of coastal flood on built environment.

For this assessment, pre-existing coastal flood maps from the Global Flood Maps dataset, openly available via the Microsoft Planetary Computer and produced by Deltares, were utilized. Initially, the ECFAS Pan-EU Flood Catalogue was considered, as it provides flood and velocity maps for the European Union's coasts and the associated forcing parameters. However, this dataset presented limitations: its highest return period was only 50 years, and it lacked representation of the Azores region. Consequently, the Global Flood Maps dataset was selected as the primary input.

This dataset includes two scenarios: one representing present-day climate conditions (circa 2018) and another projecting climate conditions for 2050 under the RCP8.5 scenario. Within each scenario, flood maps are available for extreme sea storm events of varying statistical occurrences. Return periods for coastal water levels for both scenarios are derived from an ERA5 reanalysis covering 1979–2018, offering high spatial resolution (90 m). These maps simulate coastal flooding based on three Digital Elevation Models (DEMs): MERIT, NASADEM, and LiDAR DTM. The models used to calculate the inundation maps employ a bathtub approach and account for flood attenuation, roughness, and are forced by sea levels containing surge and tide components derived from GTSM-ip6.

Urban climates are influenced by four critical factors: fabric, land cover, structure, and metabolism, which often cluster spatially within cities. This clustering allows to link urban landscape types with climate modifications, forming the foundation of the Local Climate Zones concept as defined by Stewart and Oke (2012). The LCZ classification identifies typical urban modifications of local surface climates, considering parameters like wind, temperature, and moisture. The classification groups urban environments into distinct types based on their ability to influence local climates due to their structural and distribution characteristics.

For this analysis, a global 100-meter resolution LCZ map from the Global Map of Local Climate Zones dataset (Demuzere et al., 2023) was employed for all regions except the Azores. The dataset categorizes 17 LCZ classes, 10 of which represent built environments. Each LCZ type is associated with generic descriptions of urban canopy parameters critical for modelling atmospheric responses to urbanization (Oke et al. 2017). Since the Azores were not included in this dataset, LCZ classification for the region was derived by aggregating land-cover data from the CORINE Land Cover 2018 dataset. This data provides 100 x 100-meter resolution land-use information for Europe, classifying urban areas, natural landscapes, agricultural fields, infrastructure, and water bodies. The land-use categories were mapped to corresponding LCZ classifications, creating a custom LCZ map for the Azores.

The LCZ classification also provides an estimate of the fraction of ground covered by buildings, enabling a more precise calculation of the damaged area per pixel using specific fractional depth-damage functions and country-specific maximum damage parameters. This LCZ layer serves as the exposure layer for the analysis.

Vulnerability has been approached using different damage curves based on the urban typology derived from the LCZ. While many countries have developed flood damage models based on depth-damage curves, the JRC Global Flood Depth-Damage Functions dataset offers a standardized methodology that facilitates regional comparisons. This dataset includes concave damage curves representing fractional damage as a function of water depth, alongside maximum damage values for various assets and land-use classes (Huzinga et al., 2017). These curves were developed through an extensive literature review and adjusted for continental differences. Country-specific variations in flood damage are accounted for using maximum damage values derived at the country scale, adjusted with the Consumer Price Index for 2010 and 2022.

For this analysis, three of the six damage curves available in the JRC dataset—residential, commercial, and industrial—were selected and applied to different LCZ classes based on their urban structure.

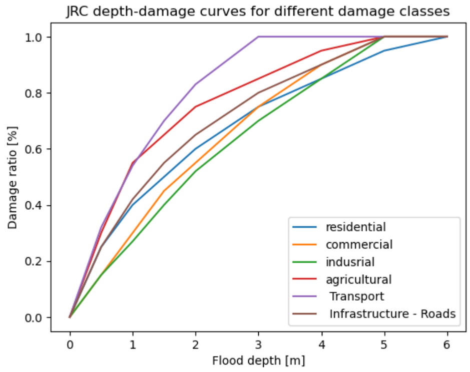

Figure 6. Flood vulnerability curves developed by Huizinga et al. (2017) and used by the JRC and CLIMAAX.

The impact for each pixel is calculated as follows:

$$Total\ Damage\ =\ \max damage\ \ \cdot \%\ urban\ density \cdot area \cdot damage\ fraction$$

Where:

- *max damage* is the country-specific maximum damage value per square meter,
- *% urban density* is the fraction of ground covered by buildings defined by the LCZ classification,
- *area* is *the pixel area,*
- *damage fraction* is the percentage of structural damage derived from the relevant depth-damage curve.

Finally, the damage values are aggregated regionally and annualized to approximate the economic losses caused by flood impacts for each region by year.

4.3.2. Results of risk of coastal flood on built environment

The analysis of coastal flood impacts and the generated risks on the built environment reveals significant regional differences in both of them. By examining the data on risk levels and annualized damage, we identify critical areas requiring intervention and adaptation efforts. The expected annual damage estimates provide a quantitative measure of the financial implications of coastal flooding. The analysis, based on depth-damage curves applied to flood inundation maps, reveals substantial disparities between regions as shown in Figure 7.

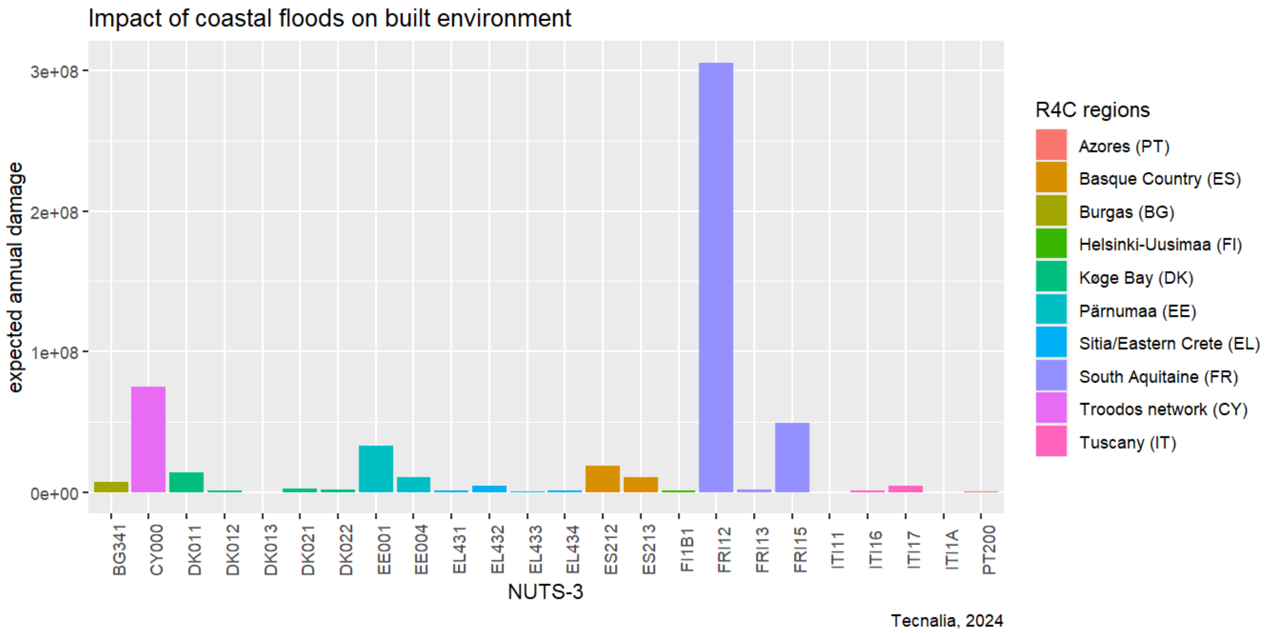

Figure 7. Impact of coastal flood on built environment in R4C regions.

South Aquitaine demonstrates the highest expected annual damage, exceeding annualized damages over 300 · 10^6 €. This is driven by the high density of built infrastructure within flood-prone areas near the city of Bordeaux and which increases both the exposure and the vulnerability. Troodos ranks second, with annual damages estimated at approximately 75 · 10^6 €, underscoring the financial vulnerability of this region to coastal floods.

Regions such as Pärnumaa and Basque Country display moderate annual damages, ranging between 25 · 10^6 € and 45 · 10^6 €. While their risk levels are not the highest, the exposure of the infrastructure and urban areas in coastal areas amplifies the financial consequences of flooding. Regions such as the Azores, Helsinki, and Tuscany experience minimal annual damages.

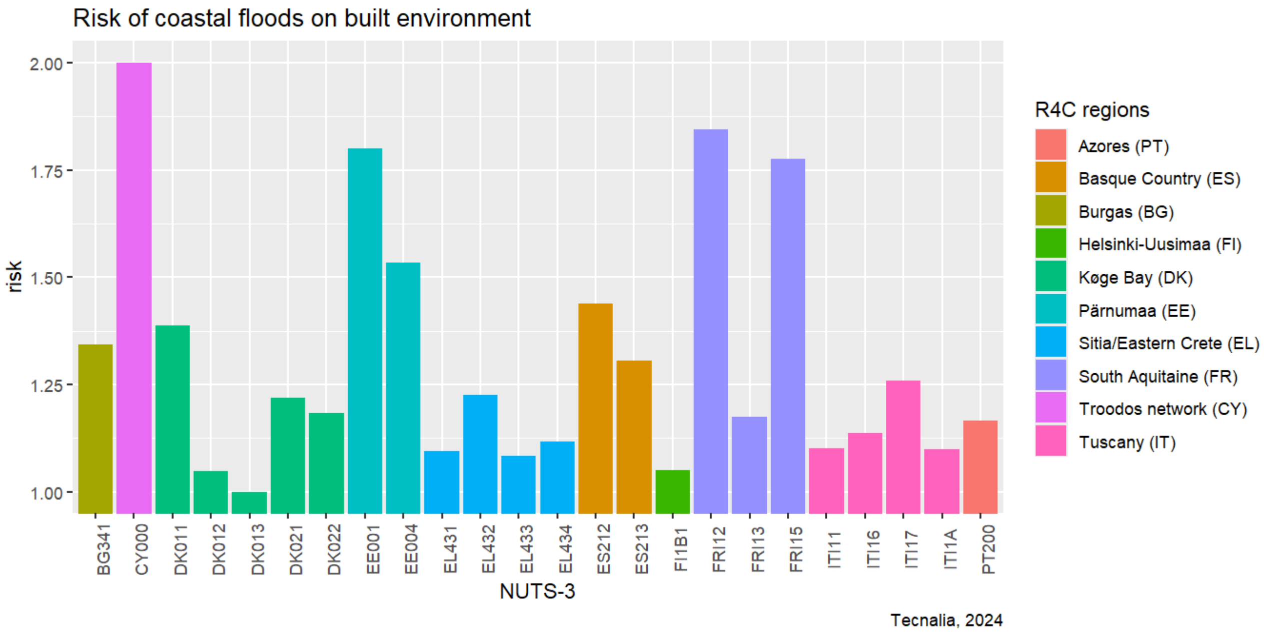

Figure 8. Risk of coastal floods on built environment in R4C regions.

A comparative analysis of risk and economic impact underscores the complex interplay between impact, exposure, vulnerability, response and adaptative capacity. Troodos, Pärnumaa, and South Aquitaine demonstrate both high risk scores and significant economic impacts, reflecting substantial exposure and vulnerability to coastal flooding. The Basque Country exhibits moderate economic impact and risk scores, but regions like Køge Bay and Burgas, in contrast, display moderate risk levels despite having low economic impact scores.

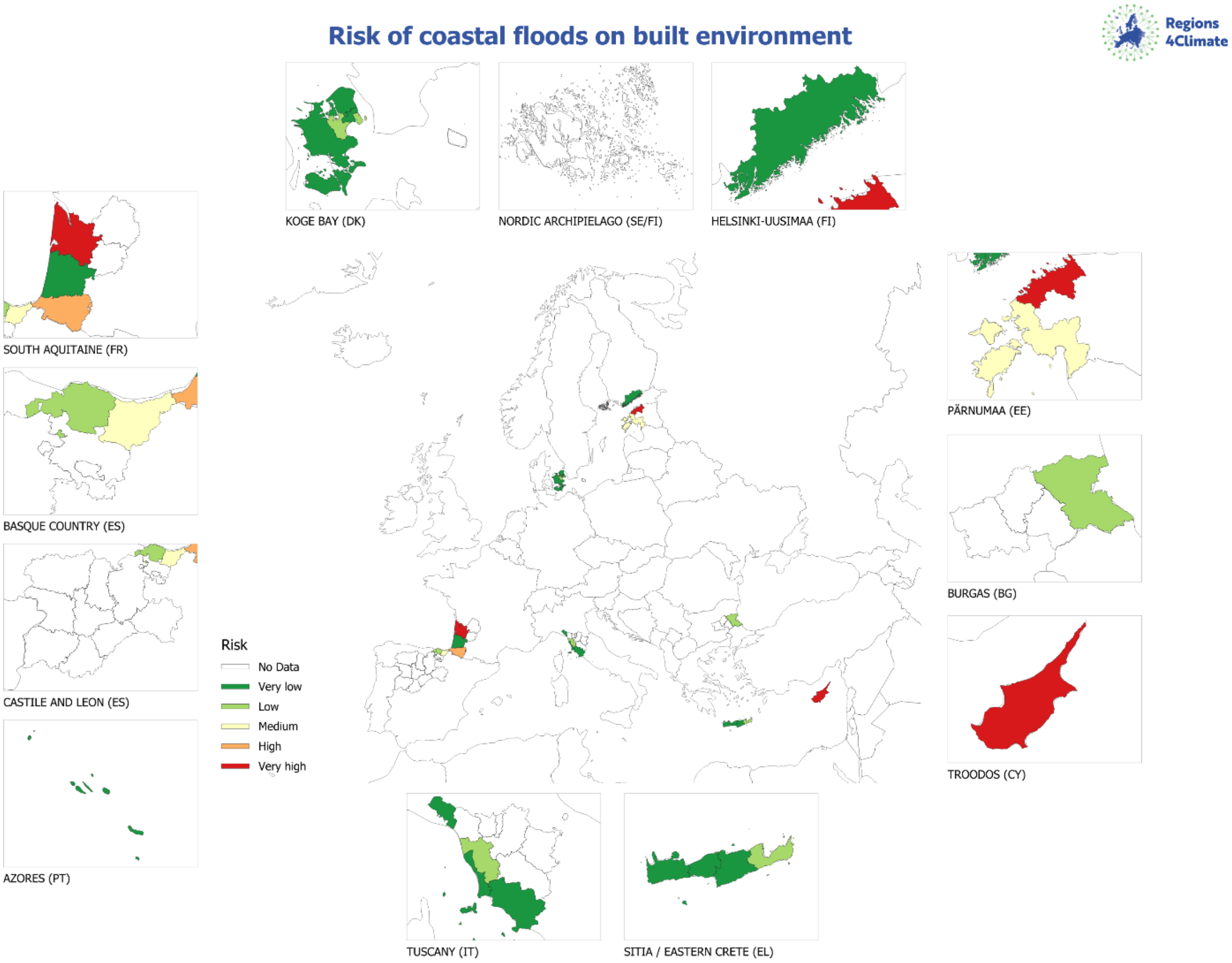

Figure 9. Map of the risk of coastal floods on built environment for every region in R4C.

4.4. Risk of droughts on agriculture activity

The methodology adopted for assessing the impact of droughts follows a hybrid approach. This approach integrates quantitative methods, such as mathematical modelling, with semi-quantitative analyses based on indicators. To characterize vulnerability and exposure, spatially explicit proxy indicators were employed. The hazard component was evaluated through the calculation of the climatic index WASP derived from simulated and observed climatic data.

The selection of indicators for three risk components—hazard, vulnerability, and exposure—was based on established methodology from the CLIMAAX Relative Drought workflow (Carrão et al., 2014) and the ESPON-CLIMATE project (ESPON, 2022), and has a multi-sectoral approach; however, the methodology proposed for R4C focuses specifically on the agricultural sector due to the interest of the regions. On the other hand, the adaptive capacity and response components will be assessed following a semi-quantitative approach.

Table 6. Datasets to quantify the impact of droughts on agriculture activity.

Potential datasets to be used in the impact analysis	
10 day accumulated precipitation sum data	Total area of harvested land in a region.
SPAM 2020 v1.0 Global data	The Local Climate Zones map is available from the Global map of Local Climate Zones.
Livestock Systems	Average livestock density in a region available from the global dataset.
Water stress	Aqueduct 4.0 Current and Future Global Maps Data from the World Resources Institute
Population counts	Population on 1 January by age group, sex and NUTS 3 region available in Eurostat
Farm counts	Farms and hectares by type of crops, utilised agricultural area, economic size available in Eurostat.
Family farm labour	Farm indicators by legal status of the holding, utilised agricultural area, type and economic size of the farm available in Eurostat.

4.4.1. Methodology of risk of droughts on agriculture activity

To assess the climatic hazard posed by droughts, the WASP index (CLIMAAX, 2024) was selected as the primary indicator. WASP considers the annual seasonality of precipitation cycle and is computed by summing weighted standardized monthly precipitation anomalies. This index was calculated using 10-day accumulated precipitation data, which were aggregated and analysed to characterize periods of drought.

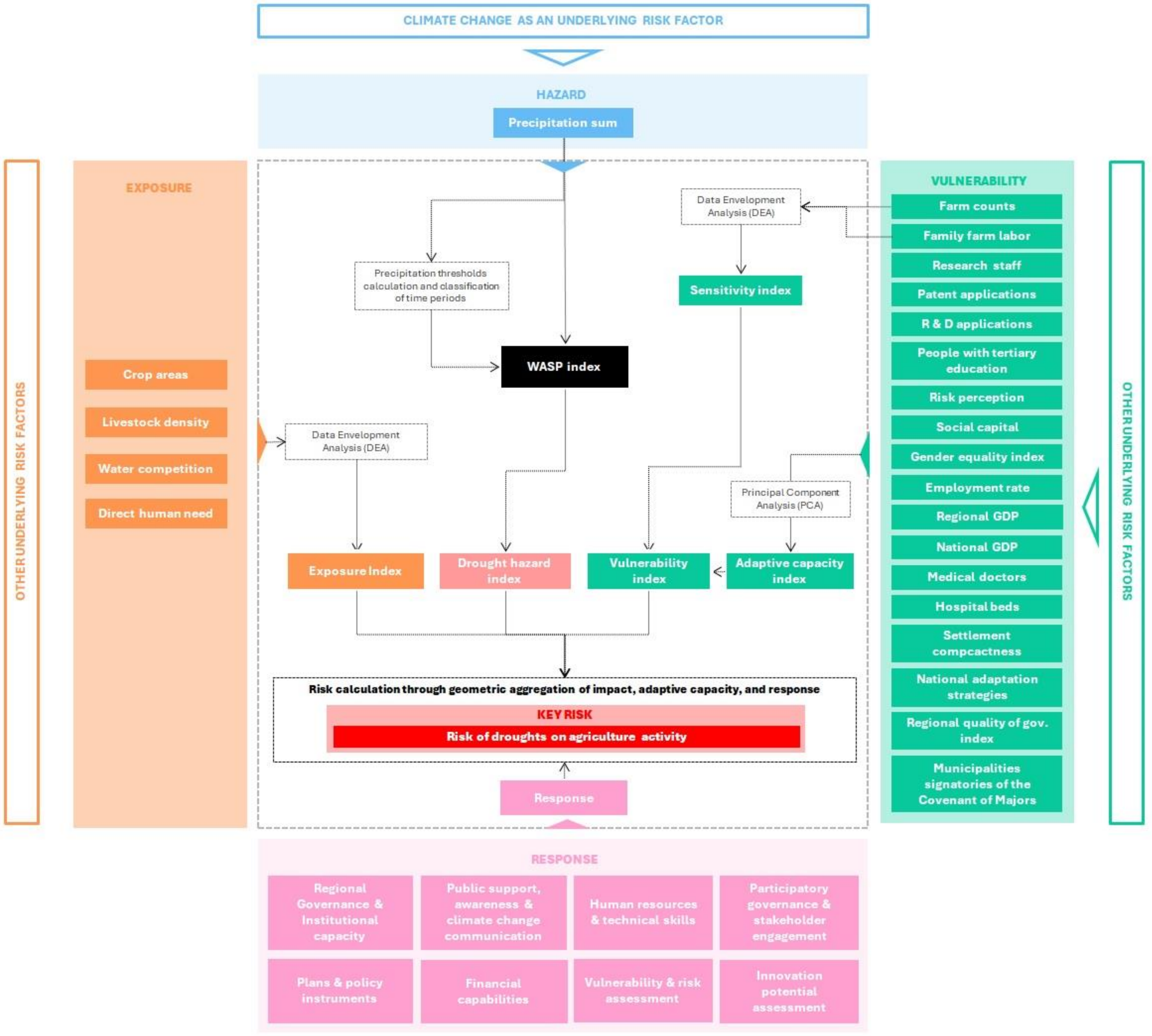

Figure 10. Methodological diagram of the risk of droughts on agriculture activity.

For the reference period (1981–2010), the precipitation data required for the WASP calculation were derived using the Watch Forcing data applied to ERA-interim reanalysis (WFDEI) methodology. This approach corrects ERA-Interim reanalysis data with observed data to enhance its accuracy. The precipitation data, downloaded in 10-day intervals, were subsequently aggregated into monthly values to align with the requirements of the WASP index calculation. This temporal aggregation is essential since WASP requires the computation of precipitation thresholds based on both monthly and annual temperature data (CLIMAAX, 2024). To ensure the reliability of these precipitation datasets, a residual analysis was conducted, examining the differences between predicted and observed data to validate their consistency and accuracy.

The WASP index was computed calculating precipitation thresholds by analysing historical annual and monthly data. Precipitation values are compared to these thresholds to classify time periods as drought or non-drought periods (Carrão et al., 2016), and then the WASP index is specifically calculated for months identified as drought periods. The severity of each precipitation deficit is calculated using the WASP formula as described by Carrão et al. (2016).

$$WASP_j = \sum_{P_{n,m} < T_m}^{P_{n,m} \geq T_m} \left(\frac{P_{n,m} - T_m}{T_m} \right) \cdot \frac{T_m}{T_A}$$

Where $P_{n,m}$ is each region's monthly precipitation, T_m is a monthly threshold defining precipitation severity, and T_A is an annual threshold for precipitation severity. These thresholds are defined by dividing multi-annual monthly observed rain using the 'Fisher-jenks' classification algorithm.

The index itself increases as a function of the duration and severity of precipitation deficits. More severe deficits result in increasingly negative WASP index values, signifying higher levels of drought hazard. Thus, the more negative the WASP index, the greater the hazard posed by drought conditions.

Drought hazard (*dH*) is estimated as the probability of exceedance the median of regional severe precipitation deficits for an historical reference period. This is represented mathematically as:

$$dh_i = 1 - P_r\{S_i \leq S\}$$

Where:

- S denotes the sorted set of severity values for all historical precipitation deficits in region i.
- S_i is the 50th percentile (median) of global severe precipitation deficits.
- dh_i represents the drought hazard for region i.

This severity is a function of the cumulative precipitation deficit and its duration, providing a robust metric for assessing the intensity of drought events over time.

For the exposure component, agricultural areas within the R4C regions are analysed in line with the CLIMAAX drought workflow specifications. Drought exposure is quantified using a non-compensatory model, which considers the spatial distribution of potential impacts on crops and livestock, competition for water, and direct human demands, such as those reflected in population size. To assess this, a Data Envelopment Analysis (DEA) is applied, which evaluates the relative exposure of each region to drought. DEA is a widely used tool for assessing the efficiency of decision-making units (DMUs) across various domains, including the measuring the relative exposure of regions (viewed as DMUs) to drought using a multidimensional set of indicators.

In this methodology, DEA examines how effectively exposure indicators utilize resources compared to other similar entities (Charnes, Cooper, & Rhodes, 1978), and a region's relative exposure is determined by its statistical positioning and normalized multivariate distance to an efficiency frontier (Carrão et al., 2016).

The sensitivity component is similarly characterized by collecting and aggregating indicators that reflect the degree to which agriculture is affected, whether negatively or positively.

To maintain consistency with the methodology, the indicator proposed by CLIMAAX (CLIMAAX, 2024) was chosen to characterize sensitivity. However, due to the lack of direct data on rural populations, two proxy indicators were selected as alternatives.

Since the required data were not available at the NUTS3 level, data at the NUTS2 scale were used, aggregated, and assigned to their corresponding NUTS3 regions. As a result, all NUTS3 regions within the same NUTS2 region were assigned identical sensitivity values. Following this process, a sensitivity index was calculated.

4.4.2. Results of risk of droughts on agriculture activity

The analysis of drought impacts and the generated risk on agricultural activity reveals significant regional differences across Europe. By examining the risk levels, we identify critical regions that require targeted intervention and adaptation measures.

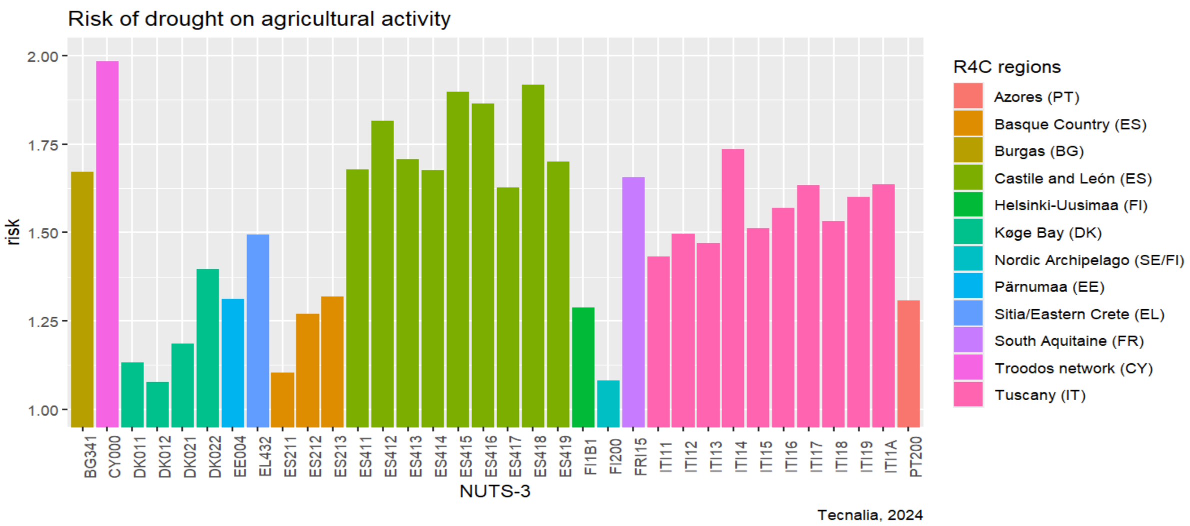

Figure 11. Risk of drought on agricultural activity in R4C regions.

Among the 12 regions analysed, Troodos and Castile and Leon show the highest overall drought risk. At the opposite end of the spectrum, Køge Bay and the Nordic Archipelago exhibit the lowest drought risk across their subregions. Regions such as Tuscany and Burgas present moderate drought risk on average, and despite the clear geographical pattern, the Basque Country shows low levels of drought risk.

The variability within regions is more substantial in certain regions like Køge Bay and Basque Country, with certain subregions facing higher risks than others. Castile and Leon and Tuscany, on the other hand, seem to have a relatively uniform drought risk across their subregions with no individual subregion standing out as particularly vulnerable.

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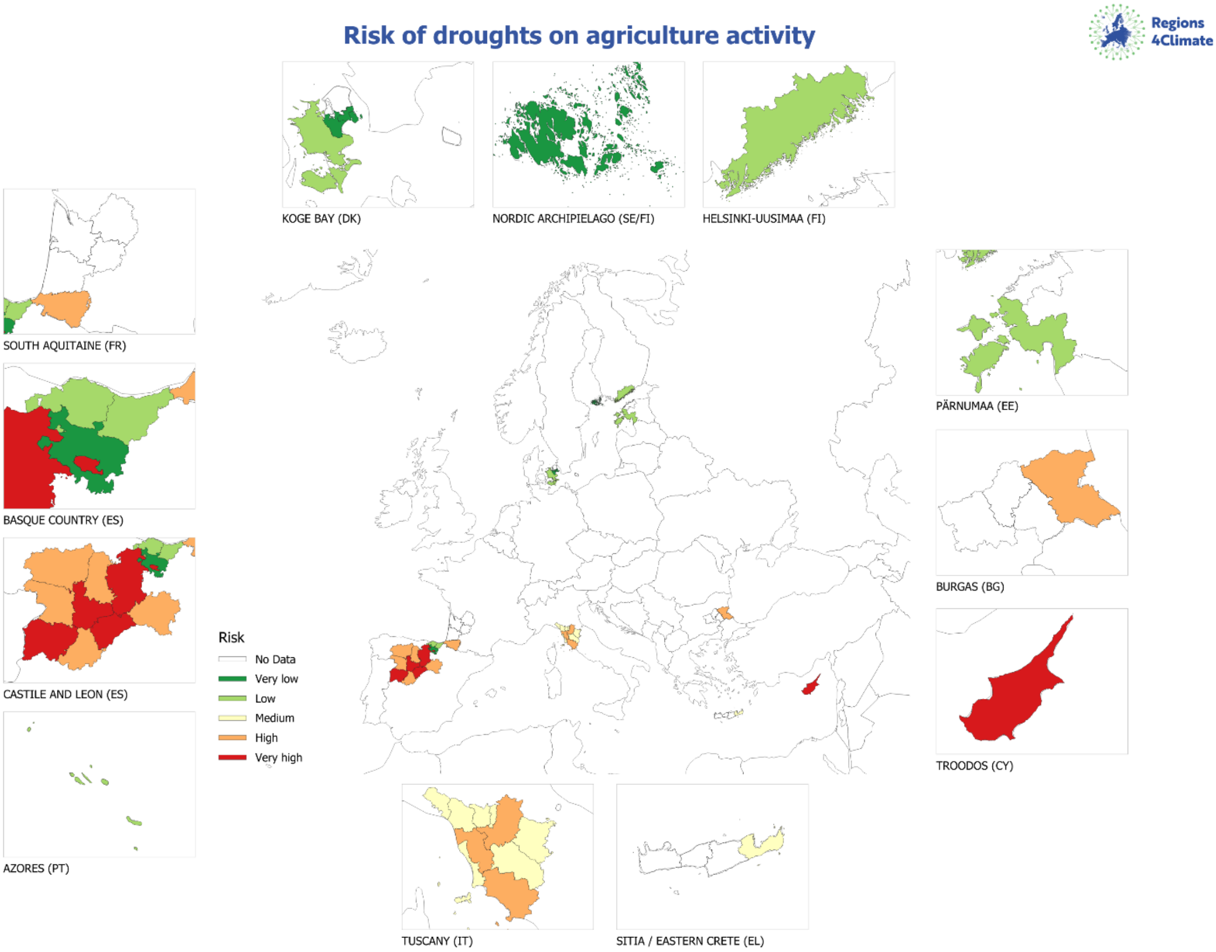

Figure 12. Map of the risk of drought on agricultural activity for every region in R4C.

The regions that are predominantly located in southern Europe, where climatic conditions, such as high temperatures and limited water availability, show a higher risk drought of agricultural activities. This a clear observable pattern in Figure 12. On the other hand, the regions situated in northern Europe, benefit from cooler and wetter climates, which naturally mitigate the impact of drought on agricultural activities.

4.5. Risk of heat-related human mortality

4.5.1. Methodology of risk of heat-related human mortality

The heat-related human mortality key risk follows a hybrid methodological approach. The quantitative part is characterised by the estimation of heat-related human mortality and the semiquantitative one addresses the components of adaptive capacity and response to risk. The methodology employed in this risk assessment does not correspond to any CLIMAX methodology, as the aforementioned project does not address the risk of heat-related human mortality.

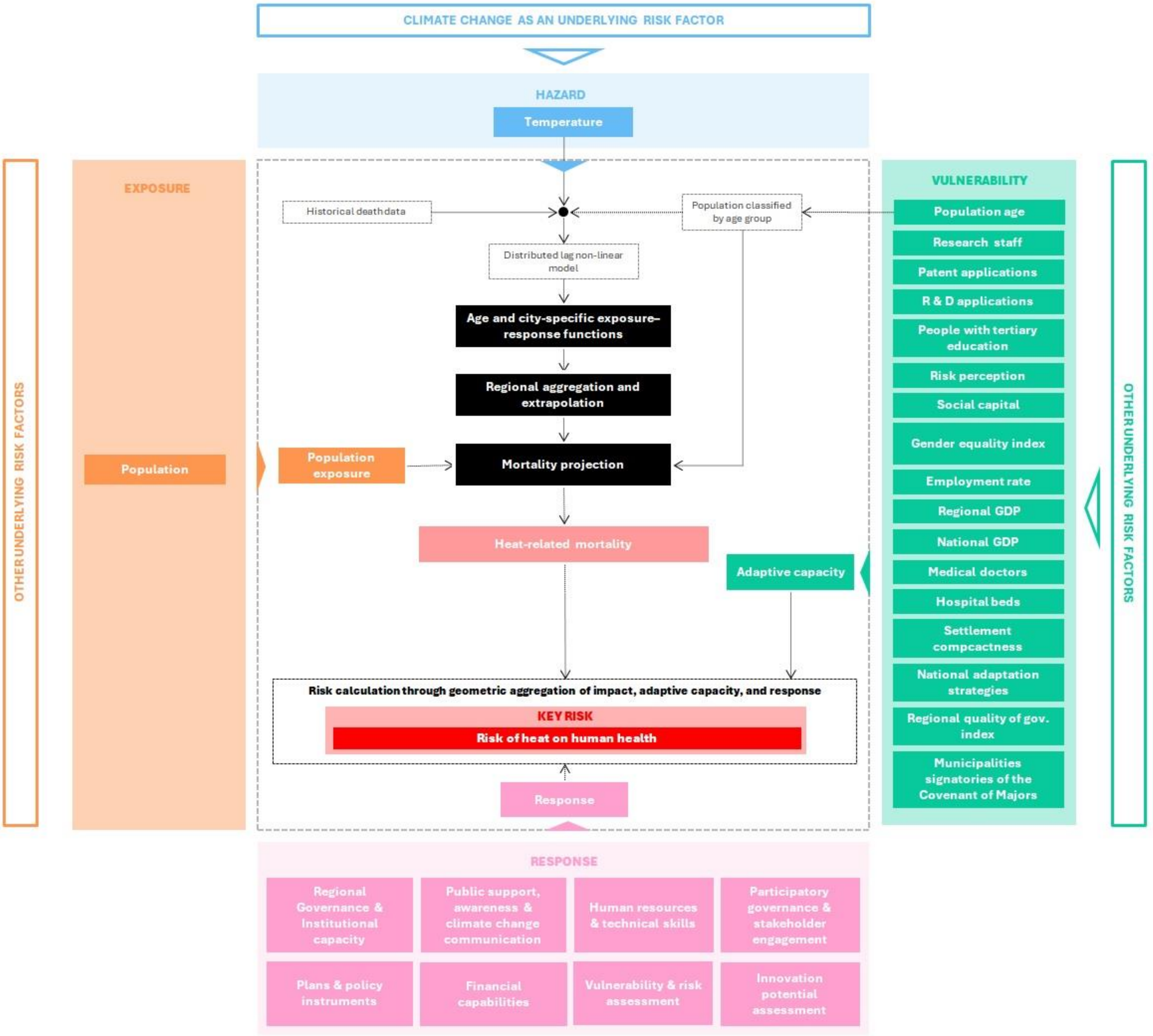

Figure 13. Methodological diagram of the risk of heat-related human mortality.

The data on heat-related mortality employed in this analysis are extracted from a recently published paper by García-León et al. (2024). In that paper, temperature-related mortality is analysed, both cold and heat, for 1368 NUTS-3 across Europe. In our case, we focus on heat-related mortality and ignore cold-related mortality. Additionally, that research takes into account age-specific characteristics and local socio-economic vulnerability. Overseas territories have been excluded from the analysis, and the Azores are therefore unfortunately outside the scope of the study.

In that research, a three-stage method is used to estimate temperature-related risk continuously across age and spatial dimensions (García-León et al., 2024). Age- and city-specific 'exposure-response' functions were obtained for a comprehensive list of 854 European cities from the Eurostat Urban Audit dataset. It is important to note that the term 'exposure-response' as used in epidemiological health studies does not correspond to the same concept of exposure and response in the field of climate change risks. Regional aggregates were calculated using an aggregation and extrapolation method that considers the risk incidence in neighbouring cities. Mortality was projected for present conditions observed in 1991–2020 and for four different levels of global warming.

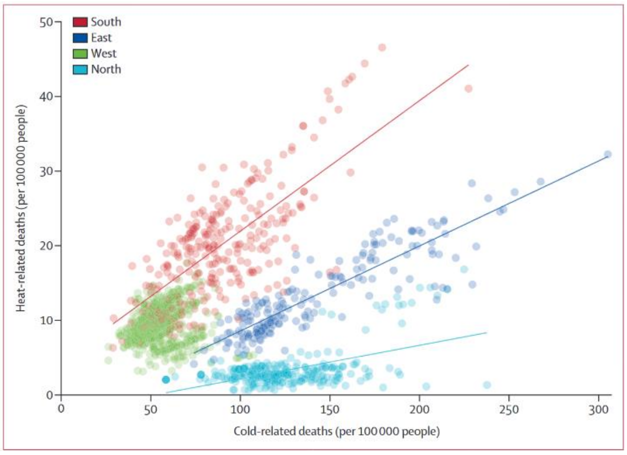

Figure 14. Patterns of temperature-related mortality in 1368 European regions (1991–2020) (García-León et al., 2024)

The epidemiological analysis is based on a distributed lag non-linear model, which can capture intricate non-linear and lagged dependencies by integrating two functions: one that outlines the standard exposure-response relationship and another that defines the additional lag-response relationship. The lag-response relationship illustrates the temporal variation in risk following a particular exposure, estimating the distribution of both immediate and delayed effects that accumulate over the lag period (Gasparrini et al., 2015). Example of association between temperature and number of deaths (Gasparrini et al., 2015) shows an example of association between temperature and number of deaths for Madrid where it can be seen how mortality increases with low and high temperatures due to cold and heat.

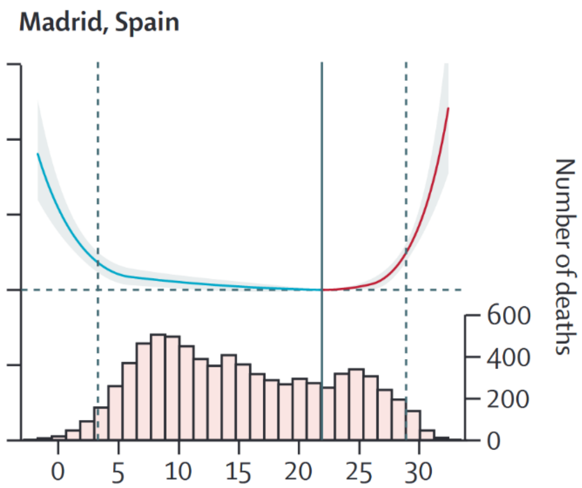

Figure 15. Example of association between temperature and number of deaths (Gasparrini et al., 2015).

The datasets used to estimate heat related mortality are included in the following 29.

Table 7. Datasets to quantify the impact of heat-related human mortality.

Datasets to be used in the impact analysis	
Temperature	Cordex-CMIP5 over Europe and E-OBS available from Copernicus Climate Change Service.
Population	Population information by age group from EUROSTAT (EUROPOP2019)

Finally, following a hybrid approach, the quantitative result (heat related deaths) is complemented with a semi-quantitative approach (adaptive capacity and response) to obtain the risk. Adaptive capacity and response components calculation have been described already in previous sections.

These different risk components are on different scales and therefore need to be pre-processed before being combined. The estimated number of heat-related deaths is standardised, normalised, and scaled into an indicator. The adaptive capacity is already scaled, and the response is scaled between the minimum and maximum values that regions can obtain from the CRML. Finally, these indicators are combined using a geometric mean, with heat-related deaths given ½ weight, adaptive capacity ¼ weight and response ¼ weight to give the final risk.

4.5.2. Results of risk of heat-related human mortality

The impact of heat-related human mortality is quantified in terms of the number of heat-related deaths, as determined by previous research (García-León et al., 2024). The figure below illustrates the mortality value for each NUTS-3 region, with colours indicating the Regions4Climate study region. The regions with the highest heat-related mortality rates are Tuscany (775), the Basque Country (211) and Troodos (82).

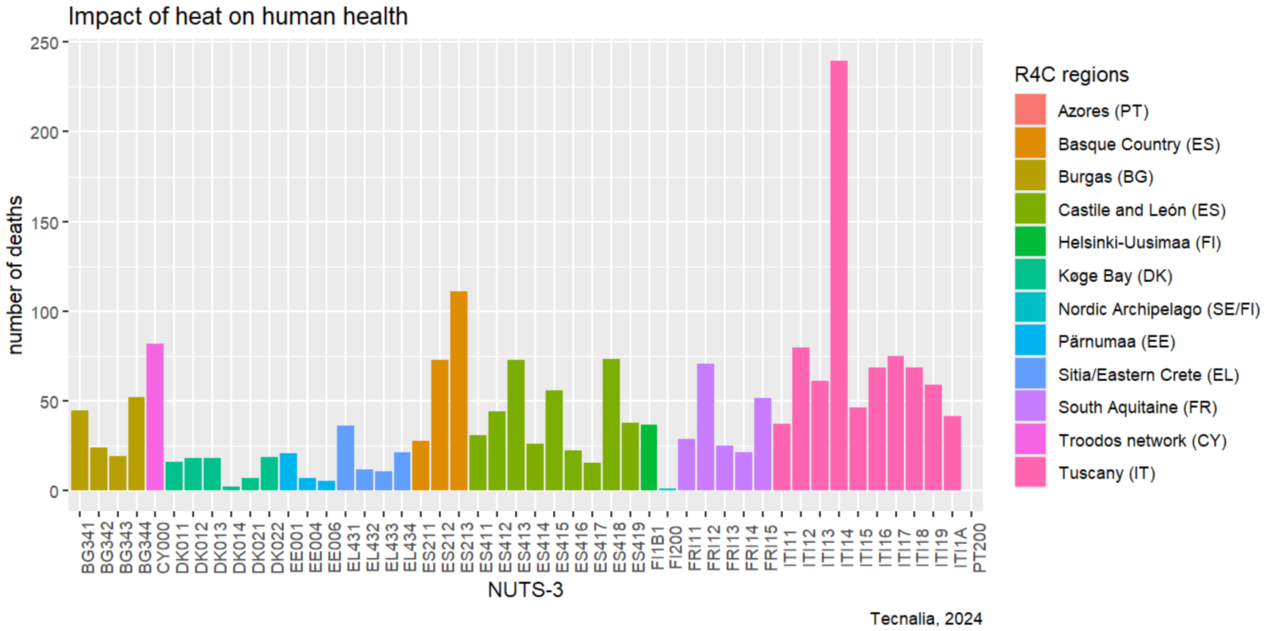

Figure 16. Impact of heat-related human mortality in R4C regions. Extracted from García-León et al. (2024).

Following this, the risk is calculated by integrating the normalized and scaled impact with the regions' adaptive capacity and response. The NUTS-3 regions with the highest risk are in Tuscany, Troodos, Castile and León, South Aquitaine, the Basque Country, and Burgas. In contrast, the lowest risk is observed in Koge Bay and the Nordic Archipelago.

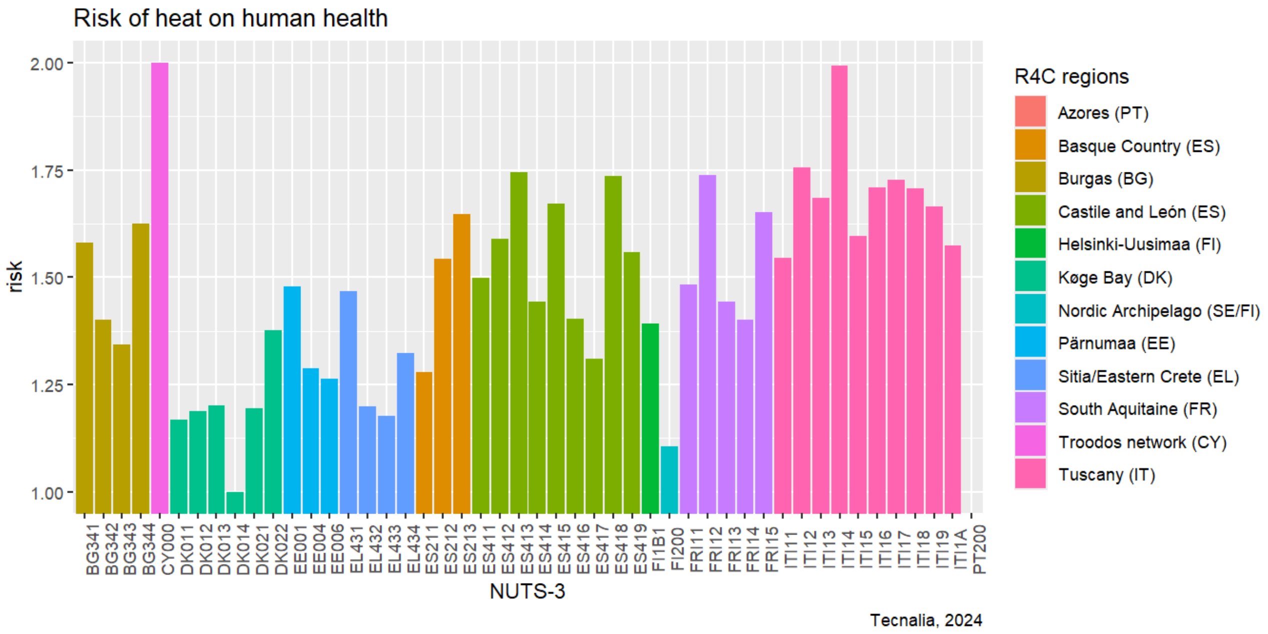

Figure 17. Risk of heat-related human mortality in R4C regions.

Figure 18 illustrates the spatial distribution of risk results. The risk levels are divided into five categories, ranging from very low to very high, with equal intervals. The map reveals that high and very high risks are predominantly found in the southern areas, whereas the northern areas exhibit low or very low risk levels.

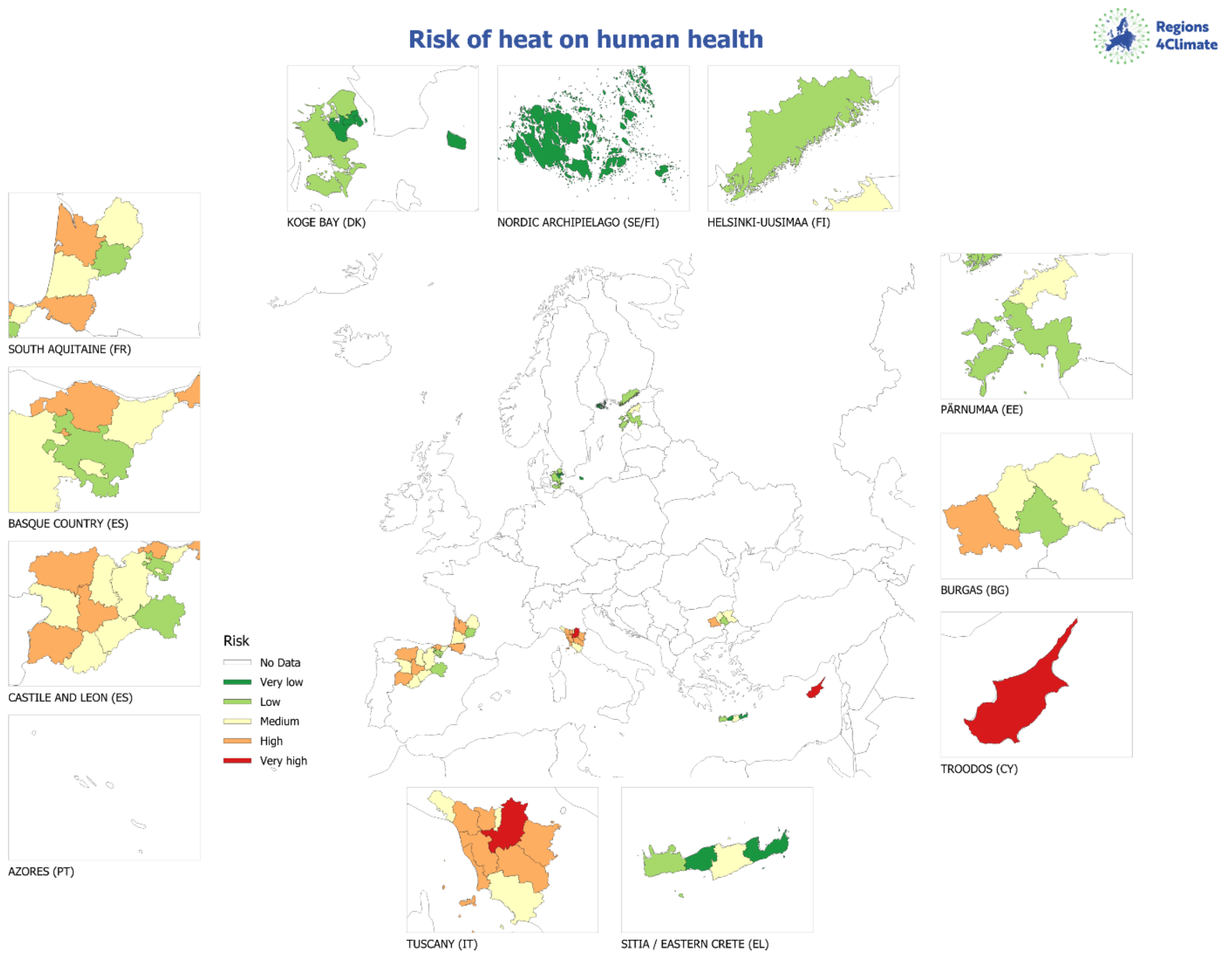

Figure 18. Map of the risk of heat-related human mortality for every region in R4C.

4.6. Risk of outdoor heat stress on human population

4.6.1. Methodology of risk of outdoor heat stress on human population

A hybrid approach is proposed to analyse this risk, combining a quantitative and a semi-quantitative model. The former, the quantitative model, is used to obtain a human heat stress value based on climatic values, while the latter, the semi-quantitative model, allows the analysis of the vulnerability of the population using a set of indicators in a holistic way. The methodology employed in this risk assessment does not correspond to any CLIMAX methodology, as the aforementioned project does not address the risk of outdoor heat stress on human population.

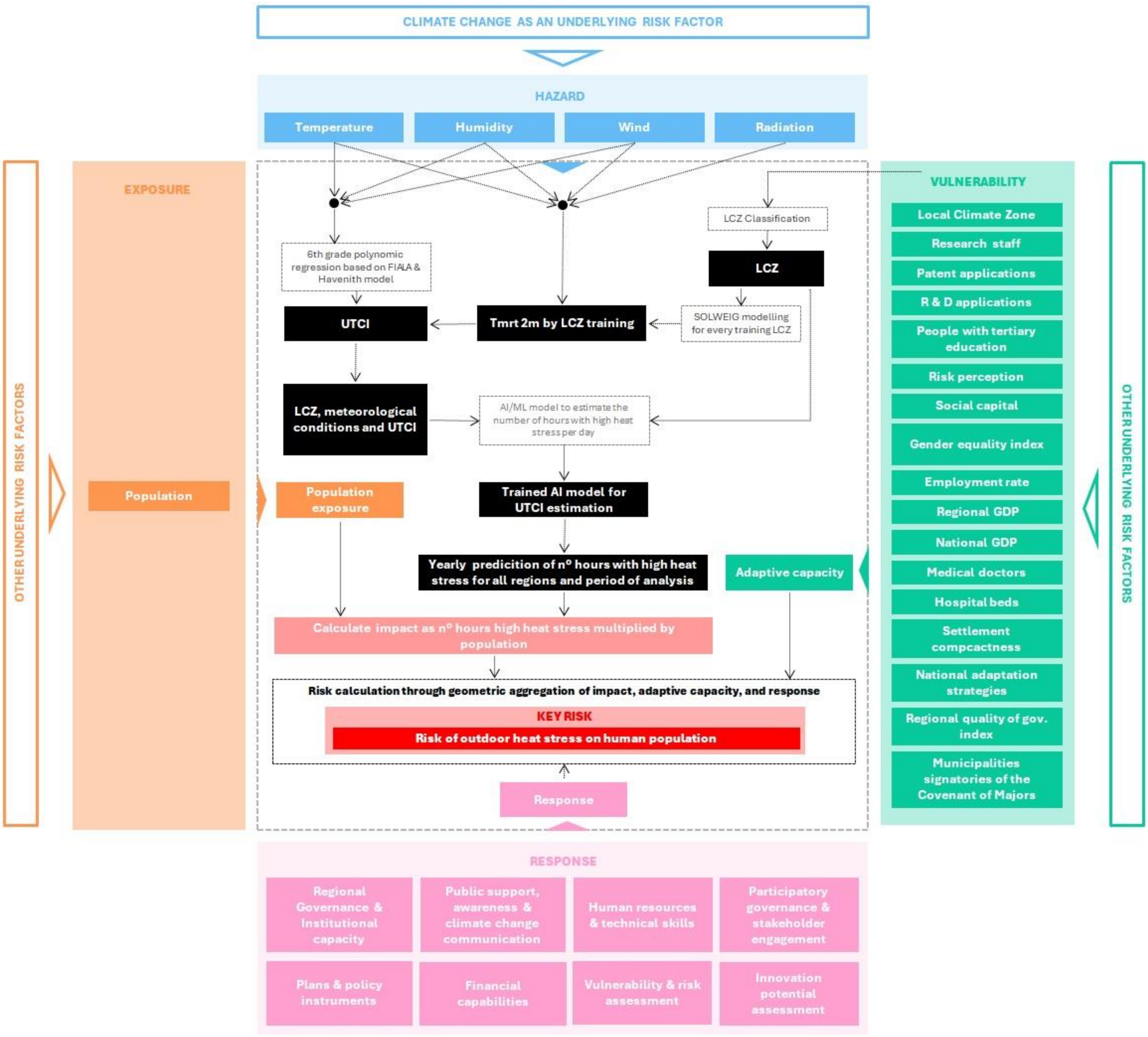

Figure 19. Methodological diagram of the risk of outdoor heat stress on human population.

The quantitative model is founded upon the concept of Universal Thermal Climate Index (UTCI), which serves as its fundamental element (Błażejczyk et al., 2010; Jendritzky et al., 2012). The UTCI has been developed since 1999 by a multidisciplinary group of experts (thermophysiology, occupational medicine, physics, meteorology, biometeorology, and environmental sciences), developed by the International Society of Biometeorology and subsequently by COST Action 730 (Cooperation in Science and Technical Development). It is based on a multi-node dynamic thermophysiological UTCI-Fiala model (Fiala et al., 2012), which analyses the thermal effects (active and passive) on the human body (for the whole body and individual parts) in a wide range of climates, combined with a thermal insulation model for clothing (Havenith et al., 2012), allowing the human energy heat balance to be solved.

Given the intricate nature of the calculations involved, the model is operationalised by a sixth-degree polynomial equation (Bröde et al., 2012), which permits the determination of a heat stress value at ten levels, ranging from extreme cold stress to extreme heat stress, through the utilisation of air temperature, mean radiant temperature, humidity and wind as meteorological input variables.

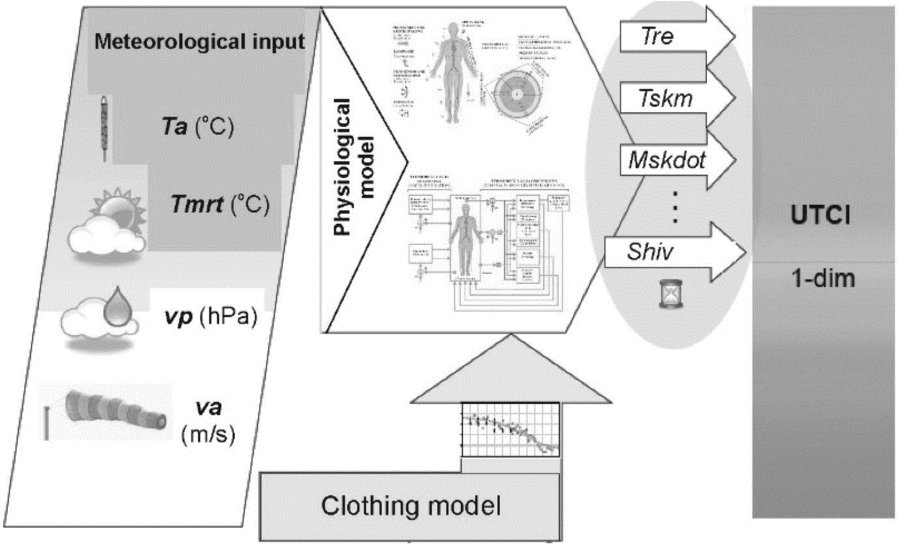

Figure 20. Scheme for UTCI model (Błażejczyk et al., 2010).

The meteorological variables required for the calculation of UTCI are typically available in meteorological databases with the exception of Tmrt. The latter is dependent on the short and long wavelength radiation received from both the sun and the ground and surrounding objects. Consequently, it is highly dependent on local conditions and has been addressed through simulation for different Local Climate Zones (LCZ) (Stewart & Oke, 2012). LCZs are a classification system that categorizes urban and rural areas based on their surface structure and cover to standardize in urban climate studies.

The Tmrt simulations for a set of selected LCZs has been carried out using SOLWEIG model (Lindberg et al., 2008) from UMEP (Lindberg et al., 2018) with hourly data from Copernicus ERA5-Land (Muñoz-Sabater et al., 2021) for the whole 2003 year. The following figure shows an example of the simulations done for one LCZ and different hours on 15th August of 2003.

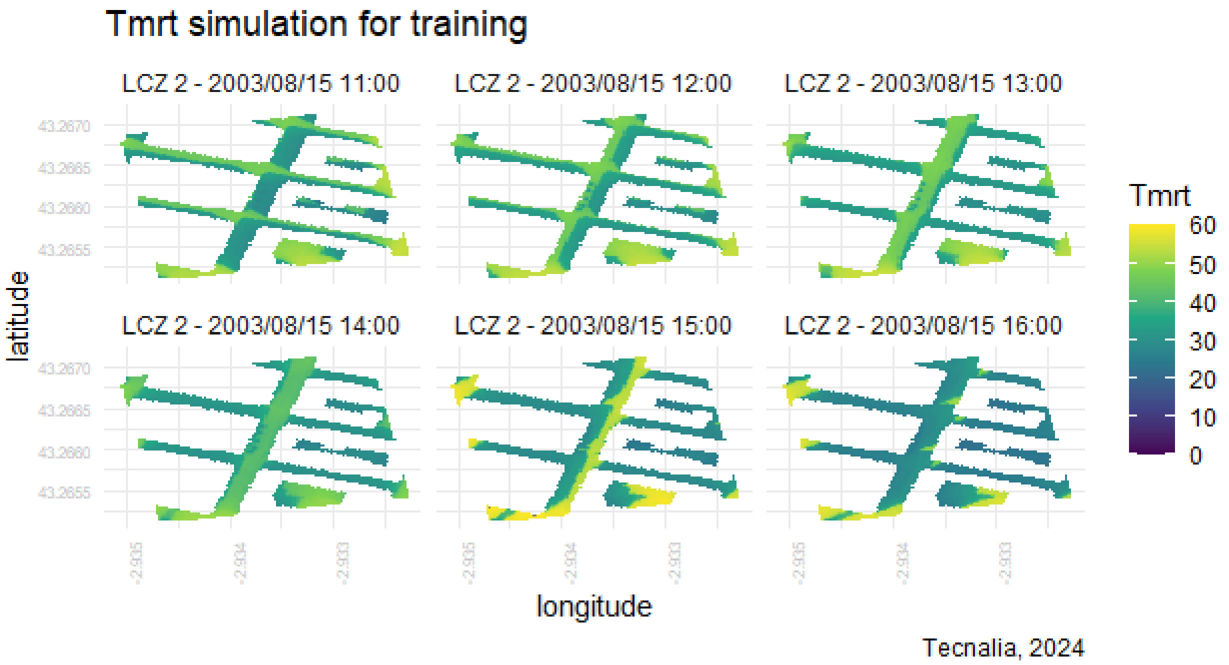

Figure 21. Time slice of one of the Tmrt simulations for training.

The Tmrt results has been used later, with the combination of temperature, humidity and wind data, to calculate UTCI through a sixth-degree polynomial equation. Then the number of hours of high UTCI per day has been calculated. This is used as the training data to develop an AI model based on a deep neural network. The model is tested using a partition of the data that is leaved out of the training and it shows an acceptable result.

The previously trained model is then employed to predict the number of hours in which high heat stress is exceeded for all regions. To this end, a 100-metre resolution LCZ (Demuzere et al., 2019) dataset and an ERA5-Land (Muñoz-Sabater et al., 2021) meteorological dataset are utilised. Once the number of hours in which the threshold is exceeded is obtained, it is multiplied by the number of people to obtain an impact value in person-hours.

Finally, following a hybrid approach, the quantitative result (person-hour with high heat stress) is complemented with a semi-quantitative approach (adaptive capacity and response) to obtain the risk. Adaptive capacity and response components calculation have been described already in previous sections.

4.6.2. Results of risk of outdoor heat stress on human population

The quantitative impact of outdoor heat stress on the human population has been established by calculating the value of person-hours with high UTCI per year for each NUTS-3 region. The regions with the highest impact, sum of its corresponding NUTS-3, are Tuscany ($2.8 \cdot 10^9$), South Aquitaine ($1.8 \cdot 10^9$), Castile and León ($1.36 \cdot 10^9$), Troodos ($1 \cdot 10^9$) and the Basque Country ($0.5 \cdot 10^9$), followed by Burgas ($0.5 \cdot 10^9$). Conversely, the regions of the Nordic Archipelago, Azores, Helsinki-Uusimaa, and Pärnumaa have the least impact.

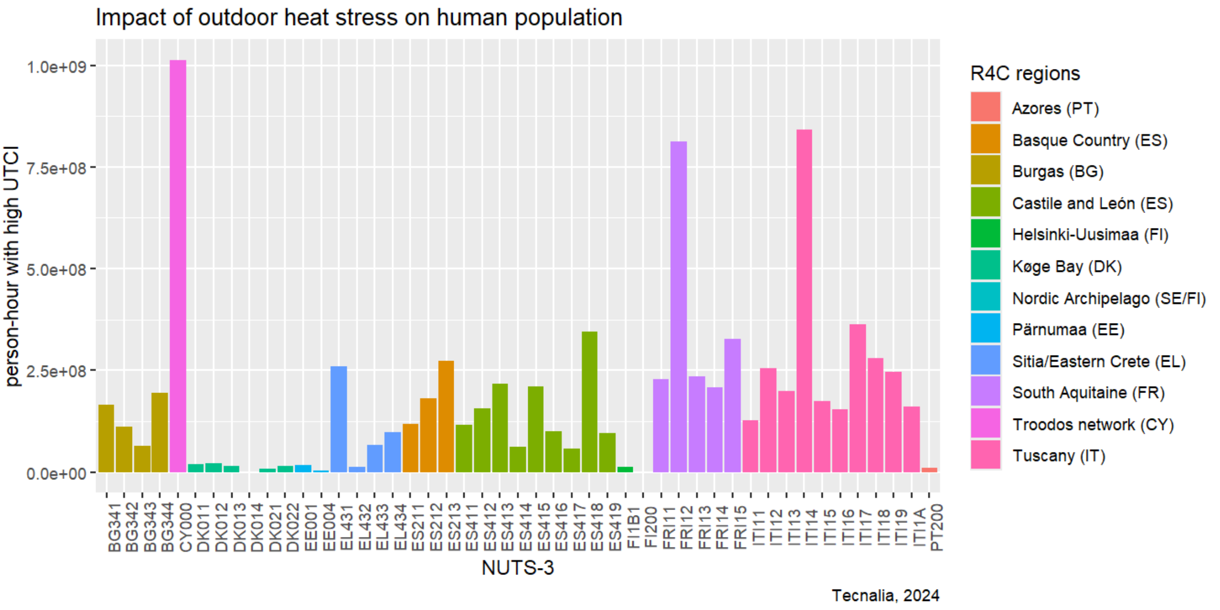

Figure 22. Impact of outdoor heat stress on human population in R4C regions.

Subsequently, the risk is derived by combining the impact, which has been previously normalised and scaled, with the adaptive capacity and response of the regions and calculated as explained in previous sections. The NUTS-3 regions exhibiting the highest risk are in Troodos, South Aquitaine, Tuscany, Castile and León, Sitia/Eastern Crete, Burgas and the Basque Country. Conversely, the lowest risk is observed in Nordic Archipelago, Helsinki-Uusimaa Koge Bay.

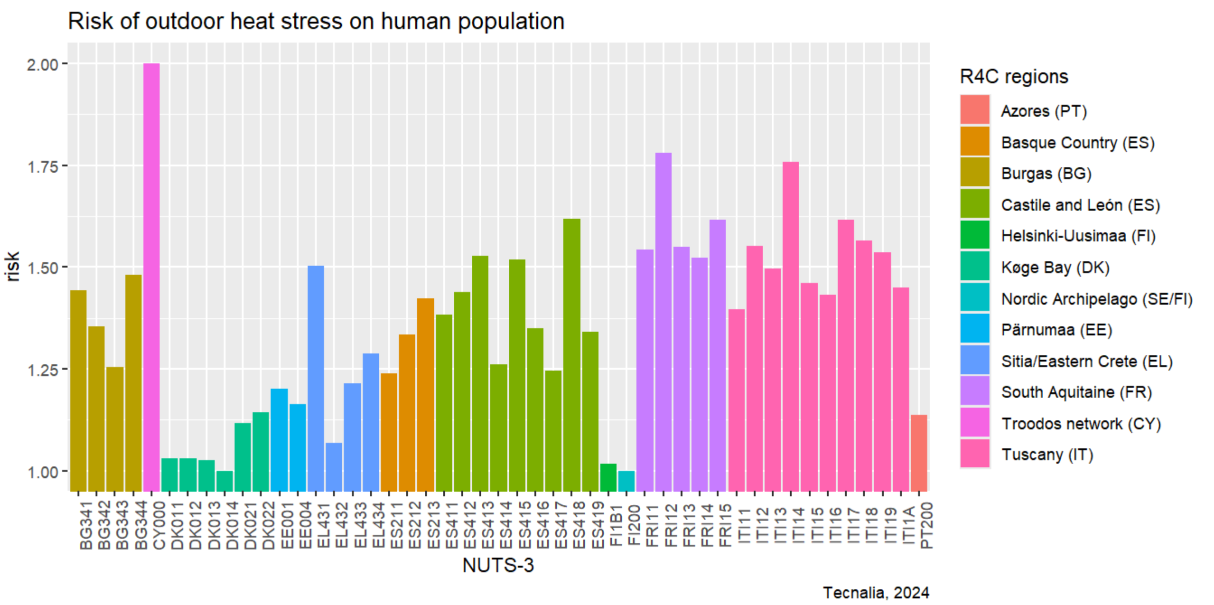

Figure 23. Risk of outdoor heat stress on human population.

The following figure shows a map of the risk results showing the spatial distribution. The risk is classified into five levels from very low to very high with equal distance intervals. The map shows a spatial distribution where very high and high risks are relatively concentrated in the southern regions, in contrast to the northern regions where the risk is very low or low.

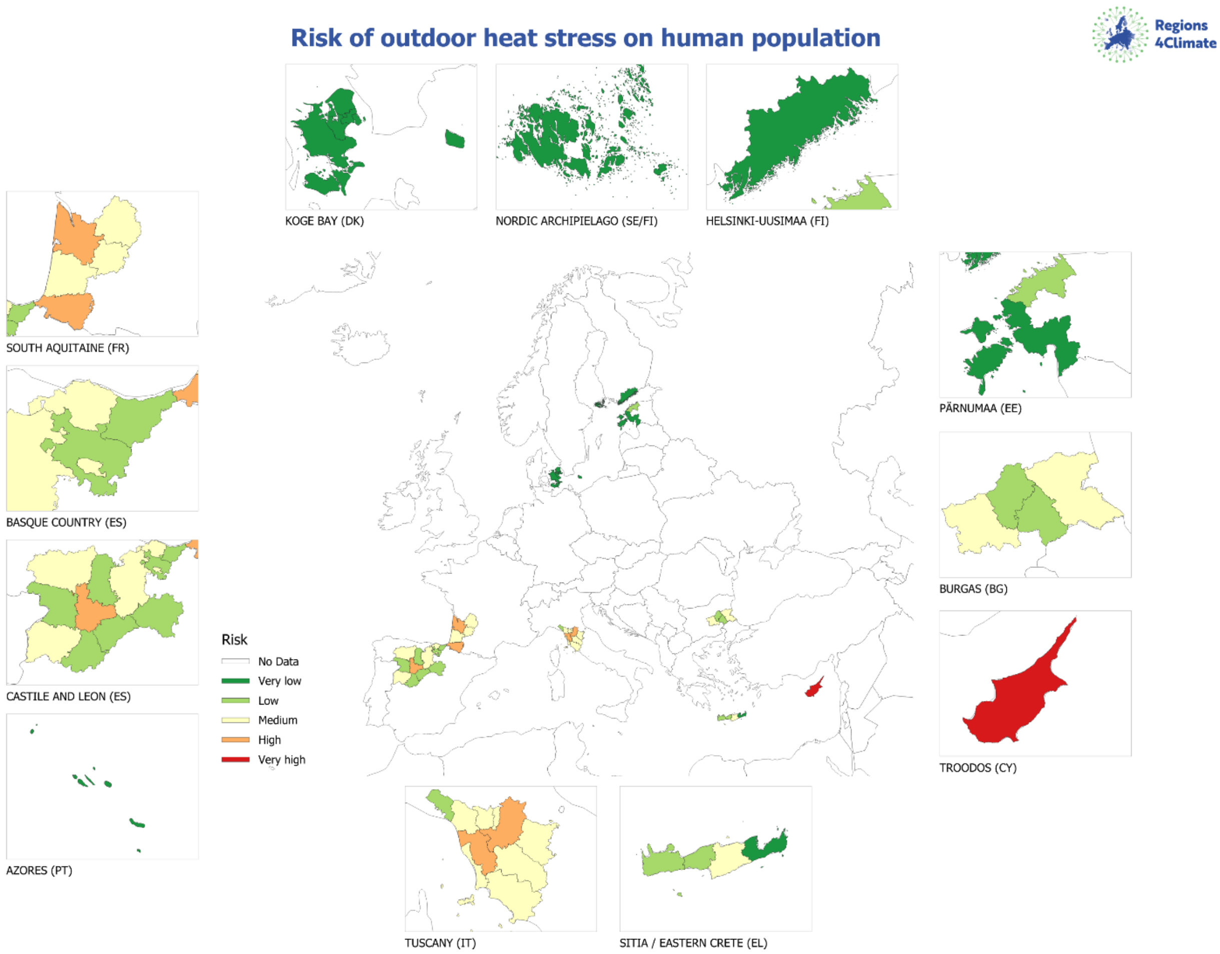

Figure 24. Map of the risk of outdoor heat stress on human population for every region in R4C.

5. Conclusions

In deliverable "D3.4 - Initial climate risk assessment" of Regions4Climate project a comprehensive and innovative framework for climate risk assessment (CRA) has been developed that integrates the latest scientific advancements and methodologies. This framework emphasizes the dynamic interaction of climate-related hazards, vulnerabilities, exposures, and responses, making it a holistic approach to assessing regional climate risks.

The objective of this risk analysis is to provide information to the regions that will be useful for adapting to the analysed risks. It must be noted that the results presented here should be interpreted with caution. In some cases, further detailed studies may be required to gain a more nuanced understanding. The input data may have inherent limitations, as may the results, due to the methodologies employed. However, it may be useful to have some understanding of the estimated potential impact, if not the precise number, at least the order of magnitude. Furthermore, it may be of value for regional stakeholders to have an indication of the level of risk compared to other regions included in the Regions4Climate analysis.

Key findings from the initial climate risk assessment include:

- **Holistic Approach**: The framework successfully incorporates multidisciplinary approaches, addressing the complex nature of climate risks and their uncertainties. It integrates concepts from IPCC AR6, UNDRR, and other relevant frameworks, ensuring a robust and coordinated assessment at the European level. It also aligns the framework with several tasks of R4C project (i.e., the D2.2. "Just transition framework" when selecting climatic scenarios and the D4.1 "Regional Resilience Maturity Model and Framework" and D2.1 "Social & economic vulnerabilities analysis" when characterizing vulnerability and response components) following a holistic perspective.
- **Hybrid Approach**: The use of hybrid methodologies, combining quantitative and semi-quantitative approaches, has proven effective in assessing various climate risks. The objective of this approach is to supplement quantitative impact models with additional factors that may contribute to the formation of risk.
- **Response component**: The incorporation of the response component, in accordance with AR6, as a fourth element of risk, alongside hazard, exposure and vulnerability, represents a novel aspect of risk analysis in these regions. This component involves the consideration of risk-informed decision making and planning (i.e., adaptation and risk reduction options) into the CRA; thus, the efforts of the regions are considered in the framework and modulate the determinants of risk. Furthermore, the response provides a bottom-up perspective in contrast to the top-down adaptive capacity based on statistical analysis.
- **Innovative Methodologies**: The most appropriate methodologies and techniques have been selected for the analysis of each risk and component. This includes the use of proxy indicators, statistical techniques like Principal Component Analysis (PCA), urban climate physical models, artificial intelligence like deep neural networks and advanced impact models.
- **Regional Specificity**: The framework is tailored to the specific needs and data availability of the partner regions, ensuring relevance and applicability. The assessment covers a diverse range of regions, from the Basque Country to Helsinki-Uusimaa, highlighting regional differences in climate risks and adaptive capacities.

- **Key Risks Identified**: The assessment has identified critical climate risks for the regions, including coastal flooding, droughts, heat-related mortality, and outdoor heat stress. These risks have been analysed in detail, providing valuable insights into their potential impacts on human health, agriculture, and urban environments.

The results of this preliminary risk assessment provide a foundation for four risks identified as priorities for the partner regions of the project. This baseline corresponds to the reference or historical period and provides relevant quantitative information on the different impacts analysed, as well as the associated risks in relative terms to the other regions analysed.

The subsequent stages of the process entail the dissemination of the findings to the relevant regional partners, the updating of the response component data by the aforementioned regions, further methodological refinements and the generation of future climate and non-climate scenarios, which will be compiled in deliverable "D3.6 – Final climate risk assessment".

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