



Deliverable D2.3 - Report on pan European vulnerability and exposure projections

WP2 – Co-design of the supporting toolbox

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Document Information

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List of abbreviations and acronyms

Abbreviation / acronym	Description
CISI	Critical Infrastructure Spatial Index
CORINE	CORINE Land Cover (CLC)
CRA	Climate Risk Assessment
CWatM	IIASA Global Community Water Model
ESM	European Settlement Map
EU	European Union
FAIR	Findable, accessible, interoperable and reusable
GAEZ	Global Agro-Ecological Zones
GDL	Global Data Lab
GDP	Gross Domestic Product
GeoTIFF	Georeferenced Tagged Image File Format
GHSL	Global Human Settlement Layer
GLW	Gridded Livestock of the World
GPW	Gridded Population of the World
GSAP	Global Subnational Poverty Atlas
JRC	Joint Research Centre of the European Commission
LAU	Local Administrative Unit
NUTS	Nomenclature of Territorial Units for Statistics
OSM	Open Street Map
RDH	The JRC Risk Data Hub
RiX	United Nations Office for Disaster Risk Reduction's (UNDRR) Risk Information Exchange
SEDAC	Socioeconomic Data and Applications Center
SHDI	Subnational Human Development Index
SoVI	Social Vulnerability Index
SSPs	Shared Socioeconomic Pathways

1 Executive Summary

This deliverable D2.3 “Report on pan European vulnerability and exposure projections” describes pan-European datasets on exposure and vulnerability collected for their use in the CLIMAAX Toolbox. It also provides the full database¹, including 111 data entries, with technical specifications of each dataset. As one principle of the CLIMAAX project is to make data Findable, Accessible, Interoperable and Reusable (= FAIR)², we strive for including only data that are publicly available.

Before presenting the database, the deliverable first defines exposure and vulnerability as two drivers of climate risk, differentiating social as well as physical aspects of these drivers. These definitions are followed by a brief overview of the operationalisation of exposure and vulnerability in current Climate Risk Assessments (CRA), including a review of current as well as future aspects of exposure and vulnerability accounted for in CRA. The database itself is presented by first describing the criteria used for data selection (FAIR principles), followed by descriptive statistics of the data records, as well as a description of the most prominent datasets used in the toolbox (see D2.4). As pan-European exposure and vulnerability data are subject to a range of limitations, data uncertainties are discussed to create awareness of these issues. Last, needs for new datasets that are currently missing are raised as well.

¹ Link to database:

https://docs.google.com/spreadsheets/d/1bQmnTUam2HNNH_3rENR7wQnmkle5xEu8N/edit?usp=drive_link&ouid=114343163831170278550&rtpof=true&sd=true

² See Deliverable 8.2 “Data Management Plan” for further information on FAIR data principles.



2 Introduction

In recent decades, the relevance of exposure and vulnerability in driving climate risks has received increasing attention in climate change research. The focus has gradually shifted from characterising hazards and their changes in intensity, frequency and spatial distribution due to climate change to potential impacts, which includes the influence of exposure and vulnerability in driving risks caused by a variety of hazards (Cardona et al., 2012; Cremen et al., 2022; Jurgilevich et al., 2017; Reisinger et al., 2020; Rising et al., 2022). Recent work has assessed this influence, finding that socioeconomic processes that drive exposure and vulnerability may contribute to climate risks to a larger degree than changes in hazards due to climate change (Harrington et al., 2021; Rohat, Flacke, Dosio, Pedde, et al., 2019; Rohat et al., 2020; Winsemius et al., 2016). In Europe, such processes include population decline and ageing populations due to low fertility and mortality rates; sprawling urban development due to high urbanisation rates; and increasing assets due to high incomes and continuing economic growth (European Environment Agency., 2024; Kok et al., 2019; Rohat, Flacke, Dosio, Pedde, et al., 2019; Vousdoukas et al., 2018).

To assess current and future climate risks, accounting for exposure and vulnerability, including their potential future changes, is therefore as important as assessing current and future characteristics in hazards (Jurgilevich et al., 2017). To support such assessment, WP2 of the CLIMAAX project “Co-design of the supporting toolbox” has developed a toolbox that allows for conducting Climate Risk Assessments (CRA) for multiple hazards that are consistent across Europe – including socio-economic drivers. To ensure that the toolbox meets user needs, it has been co-designed in close collaboration with five pilot regions (i.e. Latvia, Southwest Finland and North Karelia (Finland), Žilina (Slovakia), Catalonia (Spain), Setúbal (Portugal))³. In the second phase of the project (after month 18), this toolbox will be customised for regional- to local-scale CRA in approximately fifty European regions. To guarantee consistent CRA across Europe, the first version of the CLIMAAX Toolbox integrates pan-European data on hazards, exposure and vulnerability. While hazard data are collected and presented in *Deliverable 2.2 “Report on Hazard tools of relevance to the CRA Toolbox”*, this deliverable reports on the pan-European exposure and vulnerability data collected for use in the toolbox. These datasets provide the basis for a variety of risk assessment procedures (‘risk workflows’) that are described in *Deliverable 2.4 “Report on integrated risk assessment tools of relevance to the CRA Toolbox”*.

Before the assembled exposure and vulnerability data are presented in section 4, section 3 synthesises how exposure and vulnerability are conceptualized and assessed in the current literature. Furthermore, section 5 discusses limitations of the currently available data and the need for new datasets.

³ See Deliverable 2.1 “Report on the specifications for toolbox methods” for further details on pilot needs.

3 Concepts and assessment methods

This section provides a brief synthesis of the literature regarding the current status of exposure and vulnerability research. First, the evolving conceptualization of exposure and vulnerability in relation to climate risks is described, which provides the necessary background information on the definitions of exposure and vulnerability used within the CLIMAAX project. Second, the state-of-the-art in current pan-European CRA is discussed, based on which the exposure and vulnerability database presented was assembled (see section 4).

3.1 Exposure and vulnerability as drivers of climate risks

In recent years, climate impacts research has shifted from conceptualizing vulnerability as an outcome of exposure, sensitivity and adaptive capacity to vulnerability as a driver of climate risks that includes sensitivity and adaptive capacity. This shift has taken place from the IPCC's Fourth Assessment Report (AR4), which largely focussed on the physical impacts of climate change (IPCC, 2007), to the Fifth Assessment Report (AR5) where risk results from the interaction of climate hazards, exposure to these hazards and vulnerability of the exposed elements (IPCC, 2014; Oppenheimer et al., 2014). This conceptualisation of risk was first introduced in the IPCC's Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) (IPCC, 2012), differentiating climate processes (i.e. hazards) from socioeconomic processes (i.e. exposure and vulnerability) in driving risk (Figure 3-1a), and has been widely adopted in the CRA literature. In the Sixth Assessment Report (AR6), this 'risk propeller' was recently extended with a fourth risk driver: response (Figure 3-1b), which can include the influence of both adaptation and mitigation responses on risk (Ara Begum et al., 2022).⁴

⁴ See Deliverable 1.2 "Desk review of existing CRA frameworks" for a detailed description of recent developments in CRA.

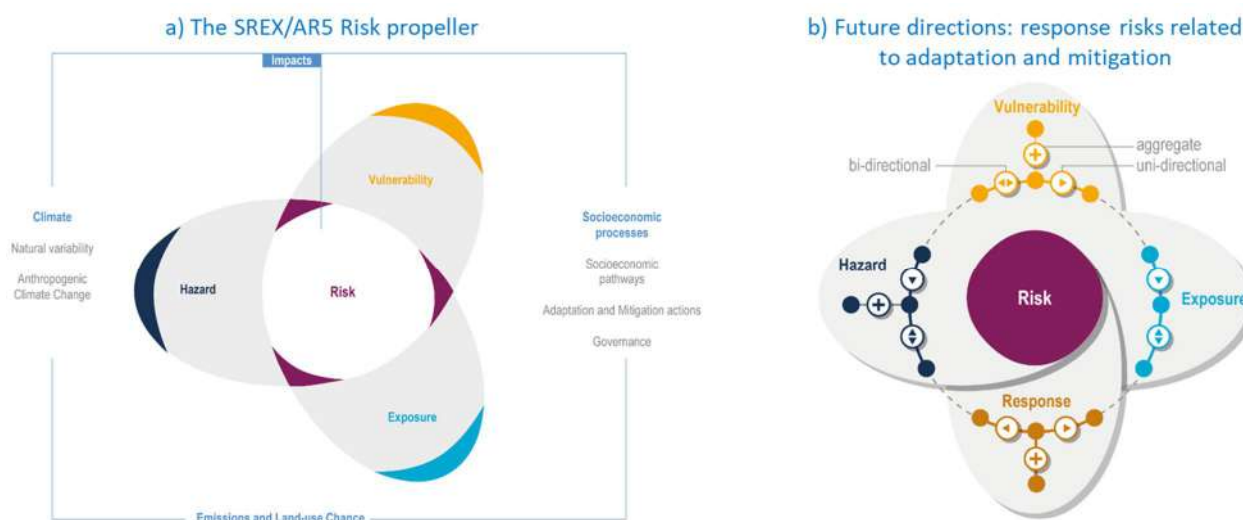


Figure 3-1 Changes in the IPCC risk framework from a) three risk drivers in AR5 to b) four drivers in AR6 (Ara Begum et al., 2022)

Within the CLIMAAX project, we follow IPCC AR6 terminology, defining exposure as “[t]he 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 is defined as “[t]he propensity or predisposition to be adversely affected. [It] [...] encompasses a variety of concepts and elements including sensitivity [...] to harm and lack of capacity to cope and adapt” (IPCC, 2023 Annex II). In this sense, sensitivity determines the degree to which a system is adversely (or beneficially) affected by climate-related stimuli (Warren et al., 2018; Zebisch et al., 2021) and may be determined by physical or societal factors of a system (Zebisch et al., 2021). Further, adaptive capacity (‘responses’ in AR6) can influence vulnerability. Adaptive capacity refers to the societal characteristics that make a community (un-) prepared to face a hazard while it is manifesting, to cope with its consequences, and to recover after it occurred. It is determined by societal factors such as: economic strength, human skills and education, technology and infrastructure, institutional capability and preparedness (Lung et al., 2013). As vulnerability describes the characteristics of exposed elements that make them more or less sensitive, both socioeconomic risk drivers directly depend on each other. However, while exposure is largely hazard-independent, characteristics that determine the vulnerability of the exposed elements can differ per hazard (Drakes & Tate, 2022; Ward et al., 2022). For instance, wooden materials make buildings more resistant to an earthquake due to their flexibility. However, they are more vulnerable to flooding events as flood waters can enter the building (De Ruiter et al., 2021).

Exposure and vulnerability can be classified based on their social and physical characteristics (Figure 3-2). This aligns with the United Nations Office for Disaster Risk Reduction’s (UNDRR) Risk Information Exchange (RiX), which catalogues data on the three risk drivers (<https://rix.undrr.org/>). The social dimension includes the population exposed to climate hazards, as well as demographic (e.g. age, gender) and socioeconomic (e.g. income, poverty) characteristics that determine its vulnerability (Cutter et al., 2003; Rufat et al., 2015). The physical dimension includes exposed assets such as settlements, infrastructure, buildings, and environmental resources along with their characteristics such as type (e.g. power stations versus schools; residential versus commercial buildings), material (e.g. wood versus brick buildings), or land use (e.g. agricultural versus industrial land) (Cremen et al., 2022; Huizinga et al., 2017; Nirandjan et al., 2022, 2024).

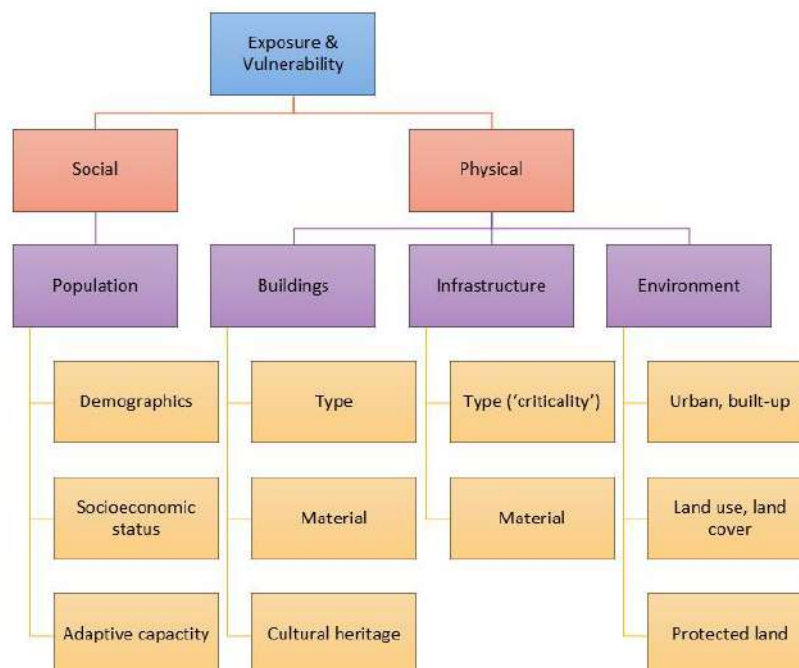


Figure 3-2 Classification of exposure (purple) and vulnerability (yellow) characteristics in CLIMAAX (own illustration)

Future changes in climate risks are not only driven by changes in hazards, but by socioeconomic developments that influence exposure and vulnerability such as population growth or decline, urbanisation and urban sprawl and progress in human development (e.g. equality, poverty reduction) (Cardona et al., 2012; O’Neill et al., 2017; Thiery et al., 2021). Furthermore, vulnerability can increase after a hazard due to the suffered damage. In the context of multi-hazards, when more than one hazard hits the same location in a short time interval, it is particularly important to account for such vulnerability dynamics (Ward et al., 2022). Therefore, it is important to not only assess current exposure and vulnerability, but to also account for temporal dynamics in exposure and vulnerability with the help of projections (Cremen et al., 2022; Jurgilevich et al., 2017; Kropf et al., 2022).

3.2 Indicators and assessment methods

This section provides a brief review of the current literature, describing how exposure and vulnerability are assessed in current pan-European CRA. It first discusses how different datasets are

used to represent different types of exposure (i.e. social and physical) for different climate hazards, both focussing on current as well as future exposure, followed by the current state-of-the-art data used for assessing vulnerability.

3.2.1 Exposure

Exposure is primarily characterized as the population or assets at risk (Harrington et al., 2021; Rising et al., 2022; Simpson et al., 2021). Indicators that are used to characterize exposed elements can be determined by the assessed hazard, for instance for heat-related risks, population exposed is the only suitable indicator to use (Rohat, Flacke, Dosio, Pedde, et al., 2019). Indicators can also be sector-dependent, e.g. using crop exposure for assessing agriculture at risk from drought (Arnell et al., 2018; Guo et al., 2016).

Social exposure (i.e. population) is the most widely assessed across hazards, with several studies analysing current exposure, e.g. to extreme heat (Tuholske et al., 2021); coastal flooding and sea-level rise (Kulp & Strauss, 2019; Muis et al., 2017); river flooding (Alfieri et al., 2017; Willner et al., 2018); and drought (Christenson et al., 2014). Assessments of future population exposure under a range of scenarios, such as the Shared Socioeconomic Pathways (SSPs), have increased in recent years. Heat (Harrington et al., 2021; Rohat, Flacke, Dosio, Dao, et al., 2019; Rohat, Flacke, Dosio, Pedde, et al., 2019) and coastal flooding (Hinkel et al., 2014; Merkens et al., 2018; Neumann et al., 2015; Vousdoukas et al., 2020) are the most widely analysed hazards, but several other studies assess future population exposure to river floods (Arnell & Gosling, 2016; Dottori et al., 2018), droughts (Arnell et al., 2018; Liu et al., 2018; Smirnov et al., 2016), and wildfire (Knorr et al., 2016).

The physical exposure of buildings is assessed across various hazards including pluvial (flash or urban), fluvial (river) and coastal floods (Iliadis et al., 2023; Nieves et al., 2022; Paprotny et al., 2021), high winds (Koks & Haer, 2020), and wildfire (Ager et al., 2021). Their geographic location primarily dictates the types and severity of risks that they are prone to face. For example, buildings in low-lying coastal regions tend to be more exposed to storm surges, those in flood plains to river flooding, and those near the wildland urban interface to wildfire. Generally, building exposure in Europe is projected to increase due to urban growth trends (Iliadis et al., 2023), as well as climate change intensifying storms and winds (Leckebusch & Ulbrich, 2004), fluvial and pluvial flood events (Bevacqua et al., 2019), and wildfire (CEU. JRC., 2017; Dupuy et al., 2020; Miller et al., 2024). In some cases, however, building exposure may decrease as climate change is predicted to lessen the effect of certain hazards in particular regions (Marcos et al., 2011). Cultural heritage sites form a special case of exposed elements, which are mainly monuments and archaeological sites, but can also be cultural landscapes or old cities. Several studies have assessed the exposure of such sites to coastal flooding and sea-level rise at global (Marzeion & Levermann, 2014), Mediterranean (Reimann et al., 2018), and African (Vousdoukas et al., 2022) scales. Regarding exposure of infrastructure, previous work has focused on airports (Yesudian & Dawson, 2021); roads and railways (Koks et al., 2019); and ports, roads, railways and power plants (Verschuur et al., 2023) under current conditions.

Exposure of different land use types such as agriculture is also assessed across a variety of hazards, with multiple studies looking at floods (Brémond et al., 2022; He et al., 2022) and droughts

(Meza et al., 2020; Ortega-Gaucin et al., 2021). Similar to building exposure, agricultural exposure is also affected by its geographic location, which can lead to different hazards of concern. Due to the projected increase in flood events (Bevacqua et al., 2019) and drought events (Spinoni et al., 2018), agricultural exposure is projected to increase. Further work assesses different land use types exposed to river flooding (Alfieri et al., 2017; Arnell & Gosling, 2016) and droughts (Arnell et al., 2018; Guo et al., 2016) under current conditions, as well as under different future land use projections (Dottori et al., 2018). For exposure of urban or built-up land, satellite-based nighttime lights can be employed for past events (Ceola et al., 2014; Mård et al., 2018), while several studies use projections of urban land to analyse future urban exposure, e.g. to coastal flooding (Güneralp et al., 2015; Wolff et al., 2020) and drought (Güneralp et al., 2015). Last, one global-scale study combines several exposed elements (i.e. land use, population and livestock) into one aggregated exposure index to characterize drought risk (Carrão et al., 2016).

Although available data of future changes in exposure have increased in recent years (see section 4), thereby addressing the need for data of future projections raised in previous research (Jurgilevich et al., 2017; Menk et al., 2022), studies accounting for these dynamics are still scarce (Cremen et al., 2022).

3.2.2 Vulnerability

In CRA at pan-European scales, studies that analyse the social vulnerability of exposed populations have been scarce (Chambers, 2020), the reason being the variety of intersecting factors that drive social vulnerability and are difficult to capture at this scale of analysis (Hinkel, 2011; Reimann et al., 2024). Several global-scale CRA derived social vulnerability estimates based on the impacts of past hazard events, however without assessing the actual drivers of vulnerability (e.g. Bouwer & Jonkman, 2018; Formetta & Feyen, 2019; Jongman et al., 2015). If social vulnerability is assessed, studies primarily use proxies to characterize vulnerability such as gender inequality (Harrington et al., 2021), economic inequality (Lindersson et al., 2023) or fatality ratios derived from reported fatalities relative to the population exposed (Dottori et al., 2018). Further, although social vulnerability is considered to be location-dependent, most CRA rely on national-level data that do not allow for the differentiation of subnational patterns in vulnerability (e.g. Aleksandrova et al., 2021; Harrington et al., 2021). The work of Rohat et al. (Rohat, 2018; Rohat, Flacke, Dosio, Pedde, et al., 2019) forms an exception: several indicators such as age, medical conditions, life expectancy, income and education are used at the subnational level to characterize social vulnerability to heat stress across Europe, additionally exploring future developments in vulnerability under the SSPs.

Current pan-European CRA primarily assess physical vulnerability, usually measured in relation to the impact on assets, e.g. through so-called damage functions (Aznar-Siguan & Bresch, 2019; Kropf et al., 2022). Damage functions assume that structures (e.g. buildings, infrastructure) will suffer a certain amount of damage based on hazard intensity and structure materials (Huizinga et al., 2017; Nirandjan et al., 2024). For example, in the case of floods, the fractional damage is related to the depth of water impacting the building (e.g. Davis, 1985). Similarly for winds, the wind intensity is related to the fractional damage to the building (e.g. Feuerstein et al., 2011; Vickery et al., 2006). Damage functions can depend on the physical characteristics of the building, including construction

material, size, height, and age as well as its use and contents (Davis, 1985; Marvi, 2020). Often such data, however, are not available at the European level, and individual functions are instead used based on the buildings' use classification (e.g., residential, commercial, and industrial) (e.g. Huizinga et al., 2017). Several pan-European CRA use damage functions to assess vulnerability of different land uses to river floods (Alfieri et al., 2017; Arnell & Gosling, 2016) and droughts (Arnell et al., 2018; Guo et al., 2016), as well as infrastructure vulnerability in a multi-hazard context (Koks et al., 2019; Verschuur et al., 2023). Such studies rarely account for future changes in vulnerability; if so, current damage functions are applied to future changes in land use conditions, for instance assessing coastal flood risk due to sea-level rise (Tiggeloven et al., 2020; Vousdoukas et al., 2020) or river flood risk (Dottori et al., 2018).

While most studies focus on either social or physical vulnerability, we found two composite indices that combine social, economic, infrastructural, political and environmental indicators: a generic hazard-independent one (European Commission. Joint Research Centre., 2023) and one for characterizing drought risk (Carrão et al., 2016). So far, further application of these two indices in pan-European CRA has been limited.

IPCC AR6 acknowledges that adaptation responses are a further important driver of risk (Ara Begum et al., 2022; Simpson et al., 2021). However, adaptation has been assessed at pan-European scale to a limited degree, as adaptation responses are a local phenomenon; hence consistent pan-European data on adaptation are currently lacking. Existing pan-European CRA primarily apply scenario-based analyses that use assumptions of adaptation strategies, thereby exploring the potential future effects of such strategies on climate risks (e.g. Hinkel et al., 2014; Jurgilevich et al., 2017; Lincke & Hinkel, 2021; Vousdoukas et al., 2018). Due to the lack of relevant data, the database presented here does not include data on adaptation responses. However, it is strongly encouraged to integrate such data in regional- to local-scale CRA in later phases of CLIMAAX where up to fifty European regions create their own customized CRA (as part of WP5).



4 Database of pan-European exposure and vulnerability data

Section 4 presents the database of pan-European exposure and vulnerability data assembled for use in the CLIMAAX Toolbox. First, the criteria used for data selection (striving for compliance with FAIR principles) are described, followed by descriptive statistics of the data records included in the database. Subsequently, we provide more details of selected datasets, with a specific focus on those data currently used in the toolbox. The full database, including detailed technical specifications, can be found under [this link](#)⁵.

4.1 Criteria for data selection

To facilitate the integration of the exposure and vulnerability data in CRA, the assembled database comprises geospatial datasets with subnational detail. The data can be either in raster format with a spatial resolution of 50 km or higher (following Lindersson et al., 2020), in vector format (i.e. points, polygons, polylines), or in table format given latitude and longitude coordinates are provided. In case that subnational datasets are unavailable, national-level datasets are included as well. The focus lies on European- to global-scale datasets that allow for a consistent assessment of climate risks across Europe. We also include data available from EUROSTAT even though data coverage is limited for non-EU member countries, therefore inhibiting consistency of CRA in non-EU countries (e.g. Turkey, Montenegro, Ukraine) as compared to EU member states. Furthermore, the data catalogued are not older than 20 years, unless they have been updated since their first publication. As an important goal of CLIMAAX is to meet the FAIR Data Principles (Figure 4-1)⁶, we focus on publicly available datasets with an open-access license that have undergone rigorous review.

Exposure and vulnerability data are inherently scattered across a wide range of repositories, websites, and data platforms, which hampers their compliance with the FAIR data principles, particularly their 'Findability' and 'Accessibility'. Nevertheless, there are a few data portals that assemble a range of exposure and vulnerability datasets such as the Joint Research Centre's (JRC) risk data hub (RDH)⁷ that provides access to data such as population density maps, building footprint datasets, and land-use classifications, particularly focussing on European NUTS ('Nomenclature of Territorial Units for Statistics') regions; the Global Data Lab (GDL)⁸ that builds on household survey data to create globally harmonized datasets related to societal development; and the Socioeconomic Data and Applications Center (SEDAC)⁹ that provides a wide range of datasets with a focus on human interactions with the environment, pursuing the goal to foster integration of

⁵

https://docs.google.com/spreadsheets/d/1bQmnTUam2HNNH_3rENR7wQnmkle5xEu8N/edit?rtprof=true&sd=true&gid=805302138#gid=805302138

⁶ See D8.2 Data Management Plan and (Wilkinson et al., 2016) for further details on the FAIR data principles

⁷ <https://drmkc.jrc.ec.europa.eu/risk-data-hub-api/docs/>

⁸ <https://globaldatalab.org/>

⁹ <https://sedac.ciesin.columbia.edu/>

socioeconomic and earth science data. Apart from data available on these data portals, we include data from scientific publications, well-established data repositories (e.g. Zenodo, Figshare), and data produced by the CLIMAAX project partners.

Box 2 | The FAIR Guiding Principles

To be Findable:
 F1. (meta)data are assigned a globally unique and persistent identifier
 F2. data are described with rich metadata (defined by R1 below)
 F3. metadata clearly and explicitly include the identifier of the data it describes
 F4. (meta)data are registered or indexed in a searchable resource

To be Accessible:
 A1. (meta)data are retrievable by their identifier using a standardized communications protocol
 A1.1 the protocol is open, free, and universally implementable
 A1.2 the protocol allows for an authentication and authorization procedure, where necessary
 A2. metadata are accessible, even when the data are no longer available

To be Interoperable:
 I1. (meta)data use a formal, accessible, shared, and broadly applicable language for knowledge representation.
 I2. (meta)data use vocabularies that follow FAIR principles
 I3. (meta)data include qualified references to other (meta)data

To be Reusable:
 R1. meta(data) are richly described with a plurality of accurate and relevant attributes
 R1.1. (meta)data are released with a clear and accessible data usage license
 R1.2. (meta)data are associated with detailed provenance
 R1.3. (meta)data meet domain-relevant community standards

Figure 4-1 Specifications of the FAIR Data Principles followed in CLIMAAX (Wilkinson et al. 2016)

4.2 Data records

The assembled [database¹⁰](#) comprises 111 exposure and vulnerability data entries, belonging to 43 distinct datasets. Of all data entries, 64 entries represent exposed elements including population (28), infrastructure (5), building footprints (3), urban or built-up land (12), and land cover (16). The vulnerability data entries (47) include variables on demographics (16), socioeconomic status (10), adaptive capacity (1), composite population vulnerability (3), infrastructure characteristics (6), building characteristics (4), urban or built-up characteristics (5), and land cover characteristics (2).

Roughly 80 % of all data entries are available at a global scale, while only 24 datasets are specific to Europe. Furthermore, more than 70 % of the recorded data are available for historical periods, reaching as far back as 1870; 14 data entries are future projections of exposure (11) and vulnerability (3) variables, up to the year 2100; and another 18 datasets provide both historical data and future projections. The spatial resolution of all data entries ranges from high spatial detail of up to 2 m to 1 decimal degree (~111 km at the equator); from individual features to different administrative unit levels; to the national level (one dataset only.)

¹⁰

https://docs.google.com/spreadsheets/d/1bQmnTUam2HNNH_3rENR7wQnmkle5xEu8N/edit?usp=drive_link&ouid=114343163831170278550&rtpof=true&sd=true

The data attributes specified in the database are aligned with the recently established Risk Data Library Standard (RDLS), which provides an open metadata standard specifically designed for datasets relevant for risk assessments (Global Facility for Disaster Reduction and Recovery, 2023). For each dataset, 30 attributes are recorded (Table 4-1), including general descriptions of the data, data type, spatial and temporal details, how the data were produced and available further resources (e.g. publications, code for data processing). By providing these technical specifications, potential users aiming to conduct a CRA are supported in selecting the dataset most suitable for their application.

Table 4-1 Attributes (i.e. column names) specified per dataset

Attribute	Description
category	category of data type
subcategory	subcategory of data type
risk_data_type	risk driver (i.e. exposure, vulnerability)
dataset_name	name of dataset
name_short	short name of dataset (if applicable)
description	short description of dataset
bbox	extent coordinates (WGS coordinates)
data_type	data type (i.e. raster, vector, tabular)
format	data format (i.e. geotiff, geopackage, shapefile, geodatabase, csv)
spatial_scale	spatial scale (i.e. global, regional, national, subnational)
coordinate_system	numerical code of the coordinate reference system (CRS) (e.g. 4326, 54009); name of CRS if code does not exist (e.g. WGS84, Mollweide)
spatial_resolution	spatial resolution (numeric value or administrative unit, feature level, country level)
spatial_resolution_unit	spatial resolution unit (i.e. arc seconds, arc minutes, decimal degrees, meters, kilometers; admin1, admin2, admin3, NUTS1, NUTS2, NUTS3)
reference_period	reference period for which the data are available (i.e. historical, future, historical & future)
temporal_resolution	temporal resolution of the data (YYYY or YYYY-YYYY; YYYY- if data are updated in real time)
temporal_interval	temporal intervals of the data (i.e. hourly, daily, monthly, yearly, 5-yearly, 10-yearly, irregular)
scenarios	name of scenarios used (if future) (e.g. RCPs, SSPs, warming levels)
data_calculation_type	method used for data calculation (i.e. inferred, observed, modeled)
analysis_type	method used for calculating the data (e.g. dasymetric modeling, random forest modeling)
underlying_data	data underlying the calculation type and approach (if applicable)
provider	name of data provider
provider_role	role of data provider (i.e. licensor, producer, processor, host)
license	data distribution license (e.g. CC0-1.0, CC-BY-4.0, CC-BY-SA-4.0)
link_website	link to the website where the data can be accessed
publication_link	link to publication (doi if possible)
publication_type	type of publication (e.g. report, article, documentation)
code_link	link to available code (doi if possible)

Attribute	Description
code_type	type of available code (e.g. for data download, processing, application)
usage_notes	any relevant information for using the data
name contributor	name of person who added the dataset to the sheet

4.3 Example datasets

In this section, we provide a more detailed description of a selected set of data from the [full database](#)¹¹, which can be chosen based on data needs in terms of spatial and temporal resolution and the underlying acquisition or modelling approach. Most of the datasets described here are currently being used in the risk assessment workflows available in the CLIMAAX Toolbox¹² (status June 6, 2024).¹³ Here we provide additional technical detail of the example datasets and provide relevant information for using the data in CRA, including datasets that reflect current as well as future conditions. It is worth noting that all datasets have different advantages and disadvantages which make them more or less suitable for a specific CRA (see section 5 for current limitations). An overview table synthesizing the technical specifications as well as the pros and cons of the data will be made available in the CLIMAAX Toolbox in due course.

4.3.1 Exposure

To characterize social exposure, a range of population datasets are available, with different spatial and temporal resolutions, such as the satellite-based Global Human Settlement Layer (GHSL) population data GHS-POP, available at spatial resolutions of 100 m, 1km, 3 arc seconds and 30 arc seconds from 1975 to 2030 in 5-year time steps (European Commission, 2023). GHS-POP spatially disaggregates census unit-level population numbers with the help of built-up land derived from satellite imagery. Further, WorldPop provides population data in annual time steps for the period 2000-2020. WorldPop spatially distributes population based on a probability per raster cell calculated with a Random Forest modelling approach (Stevens et al., 2015). GHS-POP and WorldPop are based on the Gridded Population of the World (GPW) (version 4) that have a spatial resolution of 30 arc seconds and a temporal resolution of 5-year time steps from 2000-2020 (CIESIN, 2018b),

¹¹

https://docs.google.com/spreadsheets/d/1bQmnTUam2HNNH_3rENR7wQnmkle5xEu8N/edit?usp=drive_link&ouid=114343163831170278550&rtpof=true&sd=true

¹² <https://handbook.climaax.eu/>

¹³ See D2.4 "Report on integrated assessment tools of relevance to the CRA toolbox" for further details on the risk assessment workflows.

collected from the national census and population registries. Figure 4-2 visualizes the three global population datasets for Central Europe.

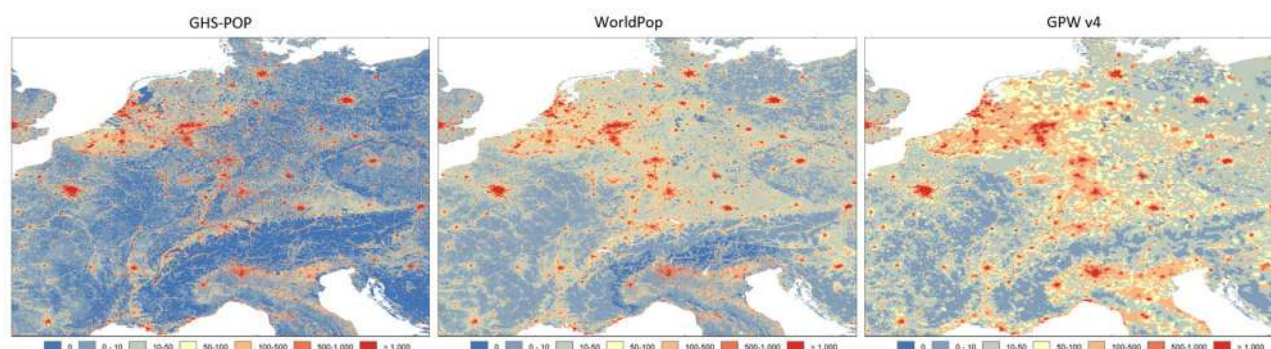


Figure 4-2 Spatial population distribution in GHS-POP, WorldPop, and GPW v4

At the European scale, several population datasets are worth mentioning. The GEOSTAT population grids have a spatial resolution of 1 km and are available for the years 2006, 2011, 2018, 2021. While the years 2011 and 2021 are based on census data, the other years use land cover data and built-up land to disaggregate the population spatially. The Historical Analysis of Natural HaZards in Europe (HANZE) database v2.0 provides population raster data at 100 m spatial resolution for the years 1870-2020, derived from the GEOSTAT data of 2011. On an administrative unit level, i.e. NUTS regions, population data are available from Eurostat and the RDH. An overview of the datasets described in this section can be found in

Table 4-2.

Table 4-2 Pan-European population datasets with technical specifications and advantages and disadvantages

Dataset	Spatial scale	Temporal resolution	Spatial resolution	Analysis type	Reference	Pros	Cons
GHS-POP	Global	1975-2030	100 m, 3 arc seconds; 1 km, 30 arc seconds	Spatial distribution based on built-up land	(European Commission, 2023)	Lightly modelled based on census data and Landsat imagery; available in 5-year time steps	Overconcentration of population where built-up land undetected (less problematic in Europe)
WorldPop	Global	2000-2020	3 arc seconds, 30 arc seconds	Random Forest algorithm	(Stevens et al., 2015)	High spatial and temporal resolution	Modelling algorithm based on several input datasets
GPW v4	Global	2000-2020	30 arc seconds	National census and population registries	(CIESIN, 2018b)	Unmodeled	Different spatial and temporal input data
GEOSTAT	Europe	2006, 2011, 2018, 2021	1 km	Derived and modelled from census data	https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution	Based on census data of 2011 and 2021	No pan-European coverage; 2006 and 2018 modelled

Dataset	Spatial scale	Temporal resolution	Spatial resolution	Analysis type	Reference	Pros	Cons
					demography/geostat		
HANZE v2.0	Europe	1870-2020	100 m	Modelled from GEOSTAT 2011	(Paprotny & Mengel, 2023)	High spatial and temporal resolution	No pan-European coverage
EUROSTAT	Europe	1960 - 2023	NUTS regions	National census and population registries	https://ec.europa.eu/eurostat/	Consistent across EU countries	No pan-European coverage

Several datasets are available to characterize physical exposure (see Table 4-3 for an overview). GHSL provides global-scale raster data of built-up land and volume, residential and non-residential settlement zones (= Morphological Settlement Zones), settlement classes, and building height at 10 m to 1 km/30 arc seconds spatial resolution and a temporal resolution of five-year time steps from 1975 to 2030 for most datasets (European Commission, 2023). It also provides built-up land data summarized at Local Administrative Unit Level (LAU) for 1975-2020 (Schiavina & Melchiorri, 2023). Open Street Map (OSM) provides spatial data in vector format (i.e. points, lines, polygons) of e.g. building footprints and types, health and education facilities, energy and telecommunication towers, and roads and railway networks (OpenStreetMap contributors, 2023). This crowd-sourced data product is continuously updated by the OSM community (see section 5.1 for more details). The

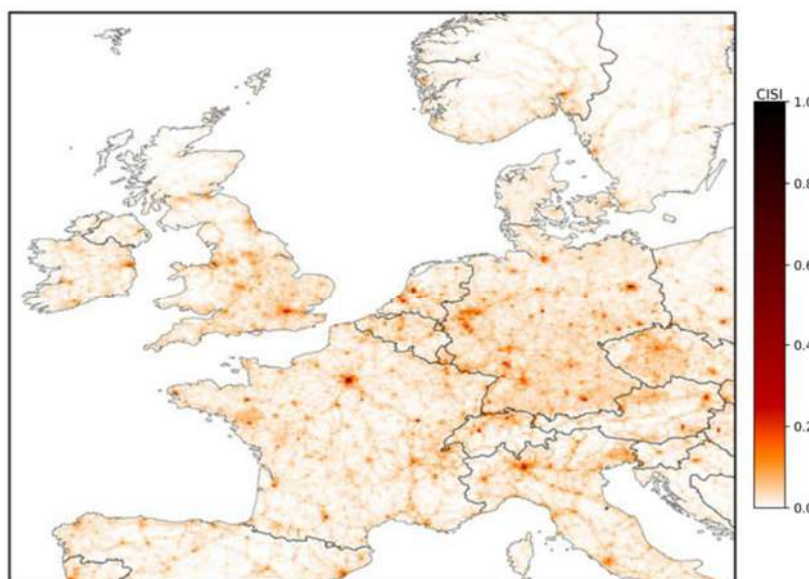


Figure 4-3 The CISI for Western Europe (adjusted from Nirandjan et al. 2022)

Critical Infrastructure Spatial Index (CISI) (Figure 4-3) is based on OSM data and is available in raster format at a spatial resolution of 0.1 degrees (Nirandjan et al., 2022).

For assessing the exposure of different land use types, the Europe-wide CORINE land cover data are available for 44 land cover classes at 100 m spatial resolution for the years 1990, 2000, 2006, 2012, and 2018 (Copernicus Land Monitoring Service, 2018). The CORINE dataset provides the basis for the higher-detail LUISA land cover map, available for 2012 and 2018 at 50 m spatial resolution.

Compared to CORINE, the LUISA Base Map delivers a higher overall spatial detail and finer thematic breakdown of artificial land use/cover categories (17 categories instead of 11 in CORINE). The LUISA Base Map can be used for multiple purposes, and it is more suitable than CORINE for applications requiring fine spatial and/or thematic detail of land use/land cover consistently across Europe, such as land use/cover accounting and modelling. Based on the LUISA land cover map of 2018 combined with OSM data, the European Settlement Map (ESM) was developed at 2 m spatial resolution, including residential versus non-residential buildings (Szabo et al., 2023). SPAM is a global crop distribution model covering 42 crops and four different technologies available for 2010 (latest) on a 5 arc-minutes crop-specific grid. The model outputs include both harvested and physical cropland. The Gridded Livestock of the World maps (GLW) show the density of eight different livestock animals in 2010 and 2015 on a 5 arc-minutes animal-specific grid and can be used to represent the exposure of animal husbandry systems. The Global Agro-Ecological Zones (GAEZ) platform provides a range of spatialised datasets for agriculture exposure and vulnerability in 2010 values. For instance, the Aggregate Crop Production Value (US\$) can be the exposure term in an agricultural drought risk assessment (Fischer et al., 2021).

Table 4-3 Pan-European datasets to characterize physical exposure with technical specifications and advantages and disadvantages.

Variable	Dataset	Spatial scale	Temporal resolution	Spatial resolution	References	Pros	Cons
Settlements	GHS-BUILT	Global	1975-2030	From 10 m to 1 km/ 30 arc seconds	(European Commission, 2023)	Global coverage; Different products (e.g. built-up land and volume, building height, residential and non-residential settlements)	Uncommon coordinate reference system: Mollweide
	ESM	Europe	2018	2 m	(Szabo et al., 2023)	Very high resolution; Distinguishes residential and non-residential buildings	Ukraine missing
Buildings, Infrastructure	OSM	Global	Most recent	Vector data (points, lines, polygons)	(OpenStreetMap contributors, 2023)	High spatial detail; Good coverage in northern Europe	Working with the data can be cumbersome (e.g. download, selection); Limited coverage in southern Europe
Infrastructure	CISI	Global	2021	0.1 degree	(Nirandjan et al., 2022)	Input data and final index in raster format; Easy to use (compared to OSM)	Low resolution
Land cover	CORINE	Europe	1990, 2000, 2006, 2012, 2018	100 m	(Copernicus Land Monitoring Service, 2018)	Relatively long time series	Fewer land cover categories or less spatial detail than LUISA
	LUISA	Europe	2012, 2018	50 m	(Pigaiani & Batista e Silva, 2021)	17 land cover categories	Ukraine missing

Variable	Dataset	Spatial scale	Temporal resolution	Spatial resolution	References	Pros	Cons
							Mixed land use in a cell
	SPAM2010	Global	2010	5 arc minutes	(Yu et al., 2020)	42 crops available	Low resolution
Livestock density	GLW	Global	2010, 2015	5 arc minutes	(Nicolas et al., 2016)	8 different animals	Low resolution
Competition on water	Aqueduct v.4	Global	1979-2019	Hydrological sub-catchment scale	(Kuzma et al., 2023)	Global coverage	Scaled for hydrological sub-catchments
Aggregate Crop Production Value	GAEZ	Global	2010	5 arc minutes	(Fischer et al., 2021)	Global coverage	Low resolution

It is worth noting that the POPGRID Data Collaborative (POPGRID, 2020) has developed a data viewer¹⁴ that can be used to compare a variety of global population and settlement datasets, which can ease the selection of a specific exposure dataset for the application at hand (Leyk et al., 2019).

Future projections of population until 2100 are available under a range of socioeconomic scenarios: the Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2017). Publicly available population projections datasets include those of (Merkens et al., 2016), (X. Wang et al., 2022), and (Gao, 2020), all of which are available at a spatial resolution of 30 arc seconds. However, they are based on different modelling approaches and underlying population data used as model input. For instance, the population projections of Merkens et al. 2016 were specifically developed to account for coastal migration processes. Further population projections are available from GHSL at 1 km spatial resolution (Directorate General for Regional and Urban Policy (DG REGIO) of the European Commission, 2020), or from IIASA Global Community Water Model (5 arc minutes) upon request. Projections of urban land are available for the SSPs until 2100, such as the data of (Gao & O'Neill, 2020) at 0.25-degree spatial resolution, also downscaled to 1 km (Gao & Pesaresi, 2021) (Figure 4-4), and (Chen et al., 2020), available at 30 arc seconds. Additionally, projections of different land uses are available at 30 arc seconds resolution until 2100 (Chen et al., 2022; Zhang et al., 2023), and GHSL provides projections per settlement class (GHS-SMOD) at 1 km resolution until 2070 (Kemper et al., 2022). Table 4-4 provides an overview of future projections datasets currently available.

¹⁴ <https://sedac.ciesin.columbia.edu/mapping/popgrid/>

Table 4-4 Pan-European future exposure projections datasets with technical specifications and advantages and disadvantages

Variable	Scenarios	Temporal resolution	Spatial resolution	Acquisition/modelling approach	References	Pros	Cons
Population	SSPs 1-5	2010-2100	30 arc seconds	Population growth in coastal, inland, urban, and rural locations	(Merkens et al., 2016)	Global coverage	Developed with coastal applications in mind
	SSPs 1-5	2020-2100	30 arc seconds	Random Forest algorithm	(X. Wang et al., 2022)	Global coverage	Modelling algorithm based on several input datasets
	SSP-RCP combinations	2015-2100	5 arc minutes	Global CWatM	(Burek et al., 2020)	Global coverage	Dataset not public, but available upon request
Urban land	SSPs 1-5	2015-2100	1 km	Artificial Neural Network algorithm	(Chen et al., 2020)	Global coverage	Modelling algorithm based on several input datasets
	SSPs 1-5	2000-2100	1/8 decimal degree, 1 km	Monte Carlo simulations	(Gao & O'Neill, 2020; Gao & Pesaresi, 2021)	Global coverage	Produced at 1/8 decimal degrees and downscaled to 1 km
Land cover	SSP-RCP combinations	2015-2100	30 arc seconds	Cellular automata	(Chen et al., 2022; Zhang et al., 2023)	Based on CMIP6; global coverage	Modelling algorithm based on several input datasets
Competition on water	SSP-RCP combinations	2030-2080	Hydrological sub-catchment scale	Modelled (Aquaduct v.4)	(Kuzma et al., 2023)	Global coverage	Scaled for hydrological sub-catchments

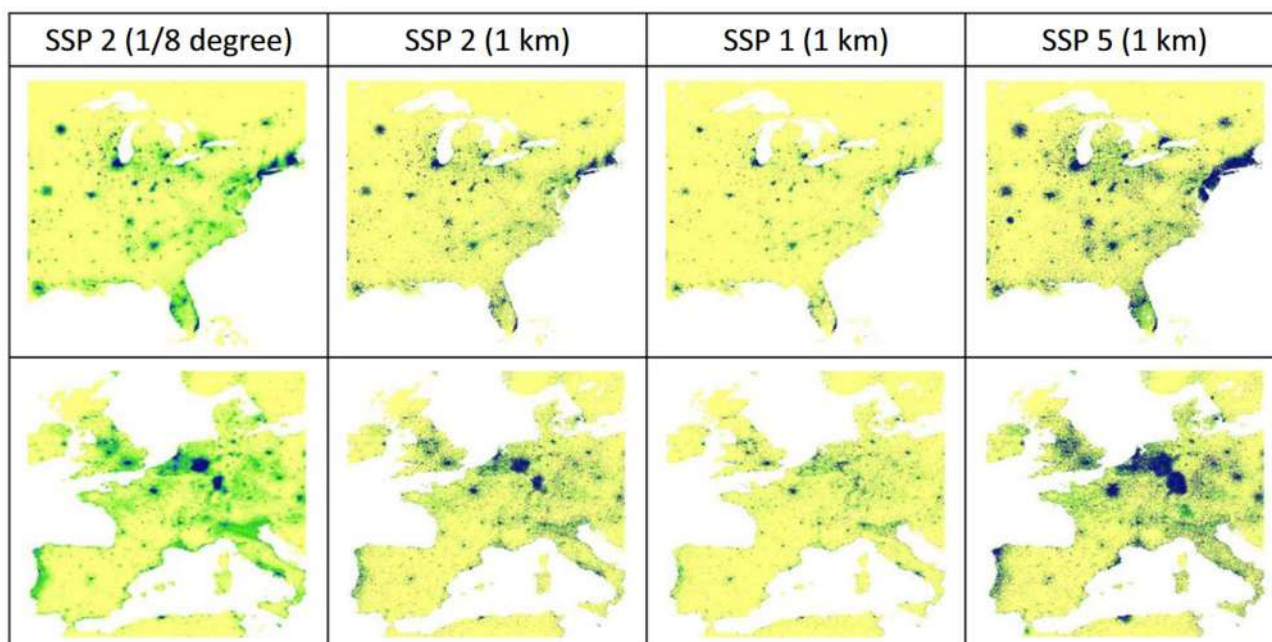


Figure 4-4 Urban land projections for North America and Europe in 2100 under SSP2, SSP1 and SSP5. Comparison of 1/8 degree spatial resolution (panel 1) to 1 km (panels 2-4) (adjusted from Gao & Pesaresi 2021)

4.3.2 Vulnerability

Although current pan-European CRA rarely assess vulnerability in a spatially explicit manner, we describe a range of spatial datasets that can be used to characterize vulnerability, including current as well as future vulnerability characteristics.

To characterize social vulnerability (see Table 4-5 for an overview), demographic data are available from the Gridded Population of the World (GPW), including age and sex raster data at 30 arc seconds spatial resolution for the year 2010 (CIESIN, 2018a), as well as for the years 2000-2020 from WorldPop¹⁵ at 3 and 30 arc seconds spatial resolution (Pezzulo et al., 2017). The subnational Human Development Index (SHDI) available from GDL further provides data on education levels, income and inequality at administrative unit level, roughly corresponding to NUTS 1 level (Smits & Permanyer, 2019). Similarly, the World Bank provides administrative unit-level data on several poverty indicators such as daily consumption and the number and ratio of poor people (Rentschler et al., 2022). The RDH includes several datasets, mainly at NUTS 2 level, which can be used as vulnerability indicators such as life expectancy, education levels, household income, and employment. Datasets can also be obtained from data produced by global models such as the GDP per capita and the percentage of rural population which are available as global grids at a 30 arc-seconds resolution from IIASA Global Community Water Model (CWatM) (Burek et al., 2020). These data are not published in an online repository but are available upon request. Although these data do not meet the FAIR data

¹⁵ <https://hub.worldpop.org/>

principles, we include them in the assembled database as they are currently used in the CLIMAAX Toolbox.

Within CLIMAAX, we have recently developed a raster-based Social Vulnerability Index (SoVI), validated with the help of flood fatalities, that combines global datasets on age and sex (GPW v4.11), education and income (SHDI), travel time to the nearest healthcare facility (Weiss et al., 2020), and settlement type (GHSL) into a composite index with a spatial resolution of 30 arc seconds (Reimann et al., 2024). The so-called GlobE-SoVI ranges from 1 to 10, with high values reflecting high vulnerability, and allows for a consistent assessment of social vulnerability across Europe (Figure 4-5).

Table 4-5 Pan-European datasets to characterize social vulnerability with technical specifications and advantages and disadvantages

Category	Indicator	Dataset	Temporal resolution	Spatial resolution	References	Pros	Cons
Demographics	Age & sex	GPW (v4.11)	2010	30 arc seconds	(CIESIN, 2018a)	Unmodeled (i.e. original census data)	Assembled from different data sources and years; No time series
		WorldPop	2000-2020	3 arc seconds, 30 arc seconds	(Pezzulo et al., 2017)	High spatial and temporal resolution	Equal distribution across administrative units
Socioeconomic status	Education; Income; Inequality	SHDI	1990-2018	Administrative units	(Smits & Permanyer, 2019)	Pan-European coverage	Limited spatial detail
	Poverty	GSAP	2019	Administrative units	(Rentschler et al., 2022)	Pan-European coverage	Limited spatial detail
	GDP per capita (current US dollar)	Global CWatM	2010-2015	30 arc seconds	(Burek et al., 2020)	Global coverage	Dataset not public, but available upon request
	Rural population	Global CWatM	2010-2015	30 arc seconds	(Burek et al., 2020)	Global coverage	Dataset not public, but available upon request
Social vulnerability	Social Vulnerability Index (SoVI)	Global Empirical (GlobE)-SoVI	~2010	30 arc seconds	(Reimann et al., 2024)	Consistent across Europe; Created from five vulnerability indicators	Limited spatial and temporal resolution of input data; Based on one global model



Figure 4-5 The Global Empirical Social Vulnerability Index (Globe-SoVI) for Europe (Reimann et al. 2024)

The assessment of physical vulnerability largely relies on damage curves, assuming that structures (e.g. buildings, infrastructure) will suffer a certain damage based on hazard intensity and structure materials. Damage curves can depend on the building physical characteristics, including construction material, size, height, and age as well as its use and contents (Davis, 1985; Marvi, 2020).

- Buildings: To do so, building materials data can be used from the PAGER database (Jaiswal et al., 2010). A recent study assembled over 1,250 vulnerability curves for different types of critical infrastructure and hazards (i.e. flooding, earthquakes, windstorms and landslides) (Nirandjan et al., 2024).
- To assess agricultural crop vulnerability to drought, the GAEZ dataset (Fischer et al., 2021) representing the share of cropland equipped for full control irrigation (%) can be used as a proxy for physical vulnerability to the occurrence of droughts and, more in general, to precipitation scarcity for the agricultural sector. The dataset has global spatial coverage and is available for the reference year 2010 at 5 arc minutes resolution.
- Road networks from OSM data can be categorized into primary, secondary, and tertiary roads, representing varying levels of vulnerability to potential wildfires. This classification can be a proxy of the proximity of roads to wildland areas outside of urban centres, with higher vulnerability attributed to roads closer to such areas.

Additionally, a set of spatially explicit vulnerability maps are available from the JRC database, which encompasses population, ecological, and economic vulnerability (Figure 4-6). These maps, featuring percentile values, can be classified based on predefined thresholds to facilitate their utilisation in a risk contingency matrix (European Commission. Joint Research Centre., 2020). The index of population vulnerability is based on the population exposed in the vulnerable Wildland Urban Interface; the index of economic vulnerability is based on vegetation restoration cost, for forest and agriculture areas; the index of ecological vulnerability is based on the ecological “irreplaceability” score (IRR) of the local vegetation (weighted average IRR) and the protected area fraction (PAF) for each burnable grid cell. The three vulnerability rasters are available at 1 km spatial resolution in Lambert Azimuthal Equal Area projection (ETRS89-LAEA).

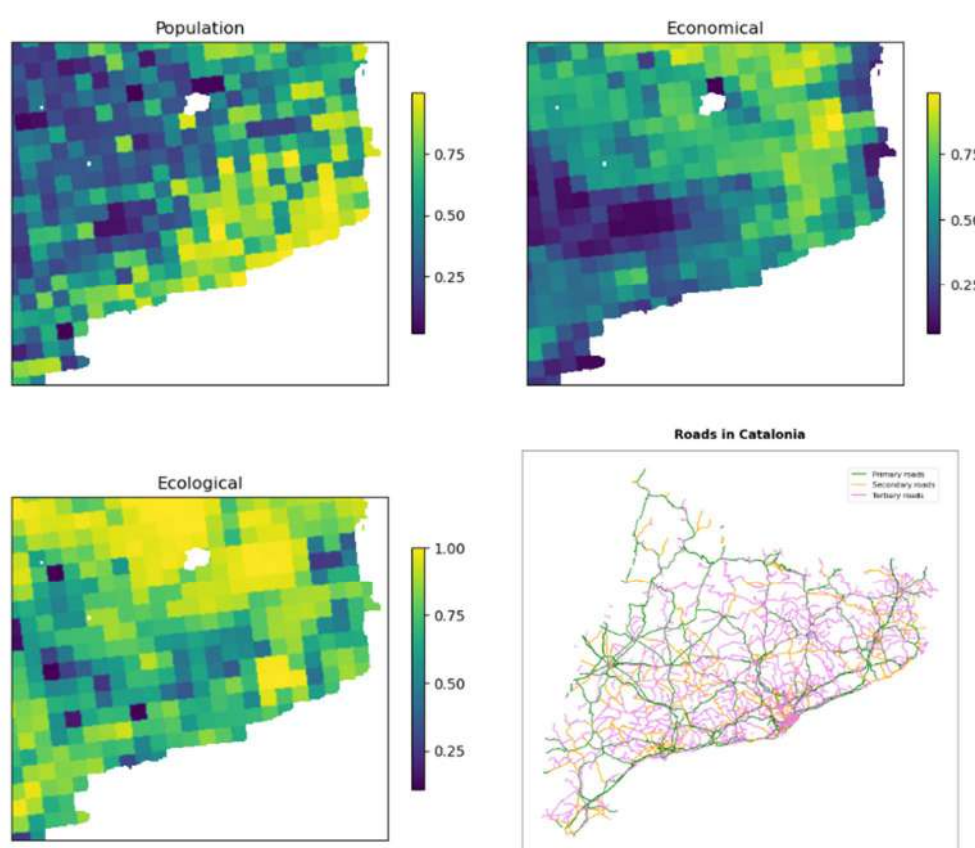


Figure 4-6 Vulnerability data (population, economical, ecological) from JRC and roads colored by level of vulnerability from OSM, for the pilot area of Catalonia

Currently, hardly any future projections of social vulnerability characteristics are available at European scale, except age and sex structure data at NUTS 2 level for a selected set of SSPs (Terama et al., 2019), which are currently not publicly available. Several global studies produced projections of Gross Domestic Product (GDP) based on spatial population projections, e.g. at 0.5 degree, 0.25 degree, and 30 arc seconds spatial resolution (Murakami & Yamagata, 2019; T. Wang & Sun, 2022). Future projections (2015-2050, 2050-2100) for GDP per capita and percentage of rural population are available as global grids at 30 arc-seconds resolution from Global CWatM. These data are aligned with the SSPs scenarios and are available upon request. Such projections can be

used as a proxy for socioeconomic status (see Table 4-6 for an overview). Further vulnerability projections that may be developed as part of CLIMAAX will be made publicly available in a well-established data repository.

Table 4-6 Pan-European future vulnerability projections datasets with technical specifications and advantages and disadvantages

Variable	Scenarios	Temporal resolution	Spatial resolution	References	Pros	Cons
Gross Domestic Product	SSPs 1-3	2010-2100	0.5 decimal degrees	(Murakami & Yamagata, 2019)	Proxy for future socioeconomic status	Low spatial resolution; three SSPs only
	SSPs 1-5	2005-2100	0.25 decimal degrees, 30 arc seconds	(T. Wang & Sun, 2022)	Proxy for future socioeconomic status	Based on quite dated population projections
GDP per capita	SSPs 1, 3, 5	2015-2050 2050-2100	30 arc seconds	(Burek et al., 2020)	Global coverage	Dataset not public, but available upon request; three SSPs only
Rural population	SSPs 1, 3, 5	2015-2050 2050-2100	30 arc seconds	(Burek et al., 2020)	Global coverage	Dataset not public, but available upon request; three SSPs only

5 Discussion and outlook

This section discusses a variety of known uncertainties related to the datasets collected in the database and described in this deliverable, which need to be considered when using these data in CRA. Furthermore, we briefly discuss currently unavailable datasets and provide a brief outlook on data under construction within CLIMAAX.

5.1 Data uncertainties

The exposure and vulnerability datasets assembled in CLIMAAX WP2 are subject to a range of uncertainties that need to be considered when using these data in CRA. Regarding observed data, climate variables often measured or based on satellite imagery, while socioeconomic data are mainly derived or modelled from other secondary data sources, particularly at continental to global scales. This is because high-resolution data (both temporal and spatial) are often not consistently available for all countries. For the pan-European data assembled here, this is particularly true for countries outside the EU, where European data reporting standards are not (yet) enforced (e.g. Turkey, Ukraine, Montenegro). As population data are derived from national census data and population registries, census intervals, and reporting periods, the quality of data collection and spatial detail of the census units differ markedly across countries, thereby limiting consistency (CIESIN, 2018b; Leyk et al., 2019). Most available population datasets disaggregate the census-based spatial population distribution to the raster cell level by using additional ancillary datasets such as built-up land, land cover, or nighttime lights, which adds another level of uncertainty to the data depending on the underlying modelling approach used (Leyk et al., 2019; MacManus et al., 2021; Figure 4-2).

Other datasets derived from satellite imagery that delineate e.g. settlements, built-up land, or buildings have the advantage of being consistent across countries due to the application of the same algorithms. However, as the characteristics of these physical assets differ markedly with regard to building materials, roof structures and settlement layouts, these data products may miss entire settlements (Leyk et al., 2018). Similarly, satellite-based data of different land use and land cover types are subject to uncertainties due to the classification algorithms used (Congalton et al., 2014). Furthermore, some exposure and vulnerability observational data are only available in dated versions. For instance, the datasets sourced from GAEZ to quantify exposure and vulnerability in agriculture are currently updated to 2010 values. This time lag between available observations and real-world conditions affects the accuracy of the analysis as it conceals the changes that have occurred in the last decade (Fischer et al., 2021).

Open Street Map (OSM) is a database of geographic information collected, maintained, and made freely available by volunteers worldwide. It encompasses diverse features such as points of interest, road networks, buildings, natural features, administrative boundaries, land use, transport networks, and utilities and services. The crowd-sourced nature of OSM can significantly impact its accuracy and completeness (Borkowska & Pokonieczny, 2022; Brovelli & Zamboni, 2018; Herfort et al., 2023; Kaur et al., 2017), both geospatially (Wechsler et al., 2019) and temporally (Singh, 2017). The level

of detail of the OSM data varies across countries and regions, and tends to suffer from less detailed information in rural, less mapped, and economically disadvantaged regions (Forghani & Delavar, 2014; Zhou et al., 2022). In addition, while the main OSM features are commonly well-mapped, smaller details may be missing or inaccurately represented (Törnros et al., 2015). OSM is updated over time, which is intended to improve accuracy and detail, but can also introduce inconsistencies (Singh, 2017). Despite these potential inaccuracies, OSM is considered the best freely available data for building and infrastructural level at a large scale. However, while OSM is representative of recent conditions, it does not incorporate projections of future changes such as new construction and urban development. Consequently, many climate change risk assessments considering buildings and infrastructure keep these factors static.

Damage functions, such as the depth-damage curves to assess flood risk (Huizinga et al., 2017), are often based on locally collected data aggregated to the global scale. This means that the global dataset mainly represents common building styles, without accounting for local details. This could be improved by including additional local information such as building types and the occurrence of rural versus urban areas. In addition, maximum damage values are represented by continent averages to allow for inter-country comparisons. For regional to local CRA, using (average) maximum damage country values from a literature review would help improve the national estimates. Please see D2.4 for further reflection on damage functions.

Regarding future projections of exposure and vulnerability data, the uncertainties in the underlying base data are compounded by uncertainties in future developments. As it is not possible to predict how society will develop in the future, a range of socioeconomic scenarios need to be considered to span the range of future uncertainty (Moss et al., 2010; O'Neill et al., 2017). Therefore, future exposure and vulnerability projections data are subject to considerable uncertainties, both in terms of underlying datasets and future socioeconomic developments.

These uncertainties need to be kept in mind when interpreting the results of a CRA conducted based on the datasets assembled in this deliverable, particularly at local and regional scales. While results will provide a reasonable first-order assessment of risk hotspots, locally developed data, for instance, from national or regional statistics offices, are needed for a more refined analysis that can inform decision-making. In this context, it is important that the data used are approved and trusted by local stakeholders (Gramberger et al., 2015; Reimann et al., 2021). As the CLIMAAX Toolbox is flexible and customizable, it is designed to accommodate other datasets accordingly. This can be achieved in the second phase of the CLIMAAX project, where European regions develop their own customized risk assessments.

5.2 Need for new datasets

As pan-European CRA have often focussed on assessing hazards, exposure and vulnerability datasets are still underdeveloped, particularly regarding future projections. Thus far, the limited availability of such data has hampered the assessment of future risk dynamics at pan-European scale (Jurgilevich et al., 2017). Therefore, spatial datasets with subnational detail are needed, particularly concerning vulnerability. This includes datasets that can be used as indicators of social

and physical vulnerability under both current and future conditions, as well as data specifically developed with the European context in mind. As vulnerability drivers may differ across hazards (section 3.1), such datasets are ideally developed separately for individual hazards. The variety of intersecting factors that drive vulnerability (section 3.2.2) make this a challenging task, resulting in considerable uncertainties in the developed datasets, which are compounded when producing future projections (section 5.1).

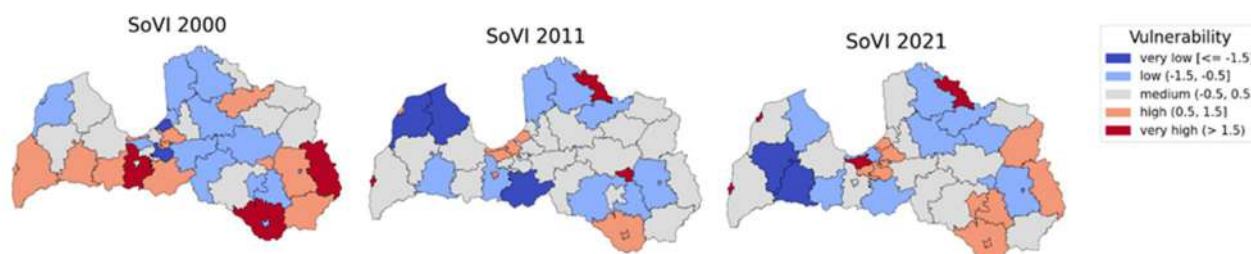


Figure 5-1 SoVI to heat waves for Latvian LAU and the years 2000, 2011, 2021. Vulnerability is represented by standard deviations from the mean.

Nonetheless, several of these needs within CLIMAAX. A team at VU-IVM is currently exploring ways to characterise social vulnerability with a focus on heatwaves, developing a Europe-specific Heat Social Vulnerability Index (SoVI) validated against heatwave fatalities^[OBJ], as well as future projections of this index under different SSPs. Once ready, these data will be made publicly available under the FAIR data principles, and we envision to include an example use case in the CLIMAAX Toolbox. Furthermore, VU-IVM is developing a methodology to calculate a SoVI to heatwaves for individual countries based on LAU data, using the Latvian pilot site as a case study Figure 5-1^[OBJ]. Also here, a methodology guide, including calculations, will be made accessible through the CLIMAAX Toolbox in the form of a Jupyter Notebook for anyone interested in assessing social vulnerability to heat. The detailed instructions will concentrate on three key areas: i) selecting vulnerability variables from available subnational data; ii) conducting literature-based and statistical analysis of the temporal dynamics of these variables; and iii) calculating a spatially explicit vulnerability index for a selected year. Additionally, examples of index validation against all-cause mortality cases, followed by identification of highly vulnerable areas prone to heatwaves using exposure and hazard maps, will be presented. The resulting social vulnerability maps can be directly used for heatwave CRA by academics, climate risk assessors, decision-makers and other relevant stakeholders with or without academic background in climate sciences. Once completed, this methodology can be applied to any European country where LAU data are available.

In addition to the data currently under development within CLIMAAX, local-scale higher-resolution data can be sourced from local authorities and statistics offices, if available. If such datasets are unavailable, locally relevant data may be developed in close collaboration with relevant stakeholders or collected with the help of crowd-sourcing initiatives, which can be particularly useful for surveying the built environment as showcased in OSM. The funding provided to the awarded European regions during the second project phase can potentially be used for the development of such case study-specific datasets.



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the European Union

6 Conclusion

The pan-European database of exposure and vulnerability data assembled as part of this deliverable provides a resource for datasets publicly available at the European scale and is the fundamental basis for the risk assessment procedures described in Deliverable 2.4. The [database¹⁶](#) covers 111 exposure and vulnerability data entries, of which 64 represent exposure and 47 vulnerability characteristics. Almost 80 % of the datasets have global coverage, while about 22 % are available at European scale, with spatial resolutions ranging from 2 m to the national level. The database includes historical data (over 70 %), future projections (14) up to 2100, as well as a mix of historical and future data (18). All data recorded in the database are subject to limitations that must be considered when selecting data for a specific risk assessment. These limitations include uncertainties as socioeconomic data are often derived or modelled from secondary data sources; rely on crowdsourcing and community-led efforts for data collection; or have varying spatial and temporal resolutions. When using the pan-European datasets for CRA at local to regional scale, results need to be interpreted with caution and should be regarded as a first order estimate of risk. It is highly recommended to use higher-resolution data from national or regional statistics offices for such applications, which the customizable CLIMAAX Toolbox is designed to accommodate accordingly.

There is still a lack of relevant data at pan-European scale that are needed for comprehensive and consistent CRA, in particular data that reflect social and physical vulnerability, as well as future projections of vulnerability. To address this gap, further research in this direction is needed as envisioned as part of the CLIMAAX project and beyond, showcased by the recent work on social vulnerability to flooding (Reimann et al., 2024) and ongoing research on social vulnerability to heatwaves in Europe and Latvia. Newly developed exposure and vulnerability data within CLIMAAX will be made publicly available under the FAIR data principles.

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https://docs.google.com/spreadsheets/d/1bQmnTUam2HNNH_3rENR7wQnmkle5xEu8N/edit?usp=drive_link&ouid=114343163831170278550&rtpof=true&sd=true

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