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This deliverable D211 is a revised version of the Modelling Framework v1.5. Table below presents the main updates between version 1.5 version1.6.

Version	Section	Date	Description
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1.6	Entire document	May 13, 2026	Added and adjusted figure names and numbers
1.6	Entire document	May 14, 2026	Final review of the document by the management team

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Abbreviations

AgERA5	Agrometeorological Indicators Derived from ERA5 Reanalysis
ALADIN	Aire Limitée Adaptation dynamique Développement InterNational
ARPAE	L'Agenzia regionale per la prevenzione, l'ambiente e l'energia dell'Emilia-Romagna
A.S.L.	Above Sea Level
ATEM	Air Pollution Dispersion Model
BVMA	Brasov Metropolitan Area
C3S	Copernicus Climate Change Service
CAMS	Copernicus Atmosphere Monitoring Service
CDD	Cooling Degree Days
CERRA	Copernicus European Regional Reanalysis
CES	Conference of European Statisticians
CHESS	Climate Hydrology and Ecology Research Support System
CLIMPACT2	An R software package that calculates climate indices
CLM	Climate Limited-Area Modelling
CMIP	Coupled Model Intercomparison Project
CORDEX	Coordinated Regional Climate Downscaling Experiment
COSMO	Consortium for Small-Scale Modelling
CRVA	Climate Risk and Vulnerability Assessment
CSA	Case Study Area
CSI	Combined Stress Index
DRS	Disaster Risk
DTM	Digital Terrain Models
DTU	Technical University of Denmark
EMO	European Meteorological Observations
ENVI-met	Microclimate simulation software for sustainable urban planning
ERA5	ECMWF Reanalysis v5
ESSL	Extreme Storm Surge Levels
FWI	Fire Weather Index
GCM	General Circulation Model
GRAL	Graz Lagrangian Model
HMD	Heat Magnitude Day
HWMI _d	Heat Wave Magnitude Index daily
ICON	Icosahedral Non-Hydrostatic Model
JRC	Joint Research Centre of the European Commission
JULES	Joint UK Land Environment Simulator
LAU	Local Administrative Units

LES	Large-Eddy-Simulation
LISFLOOD	Hydrological Model
METAR	Meteorological Aerodrome Report
NBS	Nature-Based Solutions
NCEP	National Centers for Environmental Prediction
NOA/BEYOND	National Observatory of Athens / Centre of EO Research & Satellite Remote Sensing
PET	Physiological Equivalent Temperature
PM	Particulate Matter
PREVINCAT	Service for forest fires prevention in Catalunya
RANS	Reynolds-averaged Navier–Stokes Equations
RCM	Regional Climate Model
RCP	Representative Concentration Pathways
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
UHI	Urban Heat Island
UHTI	Urban Heatwave Thermal Index
UNSEEN	Unprecedented Simulated Extreme Ensemble
UTCI	Universal Thermal Climate Index
WEI+	Water Exploitation Index+
WP	Work Package
WRF-ARW	Weather Research and Forecasting – Advanced Research WRF

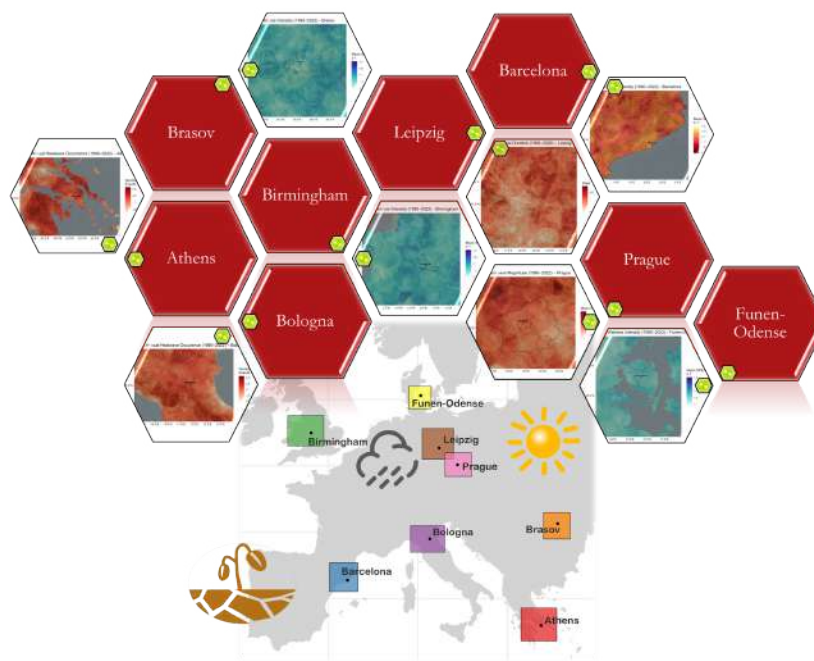
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Executive Summary



Graphical Abstract: Overview of the Climate Hazards across CARMINE Case Study Areas

This deliverable presents the initial modelling framework developed within the CARMINE project to support the characterization, analysis, and modelling of climate hazards and associated impacts across eight Case Study Areas (CSAs): Prague, Leipzig, Funen–Odense, Athens, Barcelona, Bologna, Bratislava, and Birmingham. These CSAs span diverse climatic and socio-environmental contexts across Europe and serve as Living Labs for testing and refining multi-hazard risk assessments and modelling tools. The framework established in this report aims to provide robust and harmonized approaches to identify key climate hazards, evaluate their impacts through appropriate indices, and build the foundation for actionable risk modelling and scenario generation in subsequent work packages.

The first component of the deliverable provides a concise overview of the eight CSAs, highlighting their demographic, topographic, land-use, and socio-economic characteristics. These contextual elements are essential for understanding the spatial variability of exposure and vulnerability to climate-related hazards. Each CSA represents a unique combination of urban, peri-urban, or rural conditions, and the selection reflects a deliberate effort to capture a wide range of European climatic zones, governance settings, and sectoral sensitivities.

The deliverable then examines the climate hazards affecting the CSAs during the period 1990–2022, with a focus on heatwaves, droughts, and extreme wet conditions. Analyses are conducted using standardized metrics including the Heat Magnitude Day (HMD) index and the Standardized Precipitation Evapotranspiration Index (SPEI), applied at high spatial and temporal resolution. Results indicate a general increase in the frequency, duration, and intensity of heatwaves across

all CSAs, with certain regions, such as Athens, Barcelona, and Bologna, experiencing particularly strong upward trends. Drought conditions also show increasing severity in several CSAs, while extreme wet periods are more sporadically distributed. In some CSAs, such as Brasov and Leipzig, compound events (e.g., hot-dry or cold-wet extremes) are of particular concern due to their amplified impacts.

To connect climate hazards with their potential consequences, the report introduces a set of impact-relevant indices and metrics that can serve as proxies for risk exposure. These include the Combined Stress Index (CSI), HMD, SPEI, and other derived indicators that quantify intensity, frequency, and spatial extent of hazardous conditions. The modelling approach emphasizes compound and consecutive event analysis to reflect the growing relevance of multiple, interacting climate drivers. Such metrics offer a structured way to translate meteorological observations into meaningful representations of potential stress on human and natural systems.

Disaster risk indices are constructed by combining multiple hazard dimensions, magnitude/intensity, duration, frequency, and by assessing their correlation with key impact variables. Beyond HMD, CSI, and SPEI, additional indicators such as the number of wet months, maximum wetness intensity, and compound event likelihoods provide a multi-layered perspective on hazard exposure. These indices are evaluated at the CSA level to detect local hotspots, areas of overlapping risks, and long-term shifts in event probabilities. The results show substantial intra-CSA variation, suggesting that risk is not evenly distributed even within metropolitan areas. This nuanced risk landscape supports targeted risk management and planning strategies.

To support the robustness of the derived hazard indicators, additional comparative analyses were performed using multiple climate datasets and methodological configurations. In particular, selected heatwave and drought indicators were evaluated using both EMO-1 and the lower-resolution E-OBS dataset to assess the sensitivity of temporal trends and spatial hotspot identification to the underlying climate data. The comparison showed that the main temporal and spatial patterns remain generally consistent across datasets, although local-scale differences and smoother spatial representations emerge in the coarser-resolution products.

The modelling framework established in this deliverable defines the core structure for hazard identification, index calculation, and scenario-based analysis that will be used in the development of operational tools and decision-support mechanisms in the next phases of the project, including specific urban climate applications such as the Universal Thermal Climate Index (UTCI) presented in Deliverable 2.6. In WP3, these physical risk indicators will be linked with socioeconomic data to assess local vulnerabilities, co-develop cost-effective adaptation pathways, and enable transformative adaptation planning at the CSA level. The outputs of the modelling framework will be integrated with WP4, where they serve as critical inputs for the co-development of Digital Twin (DT) simulations. These DTs will reflect the physical and socio-environmental systems of each CSA and enable virtual experimentation with cross-sectoral resilience strategies. Finally, WP5 builds upon the modelling results to enable an operational Impact-Based Decision Support Service (IDSS), offering metropolitan policy makers interactive access to locally tailored climate risk data, tools, and early warning products. This service will enhance local adaptive capacity and support implementation of science-based adaptation plans in line with EU strategies.

In conclusion, the deliverable establishes a harmonized and flexible modelling foundation for the CARMINE project, providing the methodological tools and data pipelines necessary for integrated risk analysis, stakeholder engagement, and science-informed adaptation. It delivers key spatial and temporal diagnostics of climate hazards across diverse urban contexts and sets the stage for translating scientific understanding into actionable climate services for the eight CSAs.

1. Introduction

Climate change is driving an increase in extreme weather events such as floods, heatwaves, and storms, placing cities and their populations at heightened risk. As urban areas continue to grow and concentrate critical infrastructure, the need for robust climate adaptation and resilience strategies becomes ever more urgent. CARMINE helps communities and governments prepare by creating easy-to-use tools (such as digital maps and risk forecasts) so they can make smarter decisions. The project outputs may be considered as a 'climate survival guide' for cities, designed with local input to ensure it works for the public. The CARMINE project seeks to co-create and co-develop decision-support services and guidelines to strengthen resilience and adaptive capacity to disaster risks and extreme events, with a focus on the 2023–2025 period and looking ahead to 2050. The project works in close collaboration with local communities and authorities to design and implement effective adaptation and mitigation strategies. To meet this need, downscaling techniques are used to transform low-resolution global climate model (GCM) data (typically 100–300 km) into high-resolution datasets at the kilometre scale, suitable for local or regional climate risk assessment. Because global models are too coarse to capture local climate variations, downscaling serves as a crucial bridge, delivering actionable insights for cities, farmers, engineers, and policymakers to better anticipate and manage climate extremes. The CARMINE project utilizes both dynamical and statistical downscaling approaches. Dynamical downscaling employs high-resolution regional climate models (RCMs) to simulate local weather processes in a physically consistent manner, though it is typically computationally intensive. In contrast, statistical downscaling relies on statistical relationships to translate GCM data, offering much faster results but with a greater dependence on historical data, which may overlook emerging climate shifts. The CARMINE methodology will be applied across eight selected Case Study Areas (CSAs) to demonstrate its proof of concept. Achieving this goal requires an optimal framework that effectively links global climate models with local and metropolitan scales, incorporating advancements in data, physical processes, and modelling tools to deliver innovative, user-oriented outcomes. In alignment with the objectives of WP2, Task 2.1 will focus on co-designing and establishing a high-resolution modelling framework and simulation chains that integrate physical climate and anthropogenic processes at the metropolitan scale. This approach will consider the specific climate hazards and impacts identified for each CSA, leverage the current tools available for climate and urban modelling and risk evaluation, and address data gaps and requirements for local impact modelling within each CSA.

The CARMINE modelling chain must support the local-scale hazard assessment (WP2), socio-economic vulnerabilities and risk assessments (WP3) and the co-development of decision-support tools such as Digital Twins (WP4) and Impact-based Decision Support Services (WP5). CARMINE exploits the benefits of these computational tools to model and simulate the impacts of climate change on various systems in the metropolitan regions, such as ecosystems, water resources, and human societies, to geo-design adaptation and mitigations pathways and co-develop policy recommendations to mitigate climate change impacts in metropolitan communities.

The CARMINE simulation chain for assessing climate change impacts focuses on modelling both bio-geophysical and socio-economic stressors, and is based on:

- Novel statistical/AI-based approaches for enhancing the resolution of GCMs, and consortium RCMs (COSMO-CLM, ICON-CLM, WRF) to the metropolitan scale
- Dynamical downscaling schemes of global and physical models on limited areas
- Assimilation of open-access data (Copernicus Climate Change Service, C3S, in situ data) and newly acquired data at CSA level, with improved parameterization and optimal set-up through extensive offline modelling at a very high resolution
- A hybrid modelling approach to assess local impacts with a special focus on urban areas

The modelling chain is essential for supporting the development of high-resolution risk assessment models that integrate climate, earth system processes, and socio-economic drivers, enabling richer data fusion and more effective adaptation and mitigation strategies in Europe's metropolitan regions. By co-designing, establishing, and testing an integrative modelling approach including applications of Nature-Based Solutions (NBS) at local to metropolitan scales, CARMINE supports the development of vulnerability profiles, socio-economic risk assessments, and evaluations of local adaptive capacity for climate resilience. The added value of the CARMINE modelling framework lies in its enhanced representation of local land surface characteristics, assimilation of high-resolution, open-access local data and Volunteered Geographic Information, as well as the implementation of novel optimization methods such as AI and machine learning.

Establishing this framework will enable the effective preparation and organization of new statistical and dynamical downscaling activities to be developed in Task 2.2, aimed at enhancing the resolution of climate models. It will also support the urban modelling initiatives in Task 2.3 and the hazard indicator assessments in Task 2.4. The outcomes of this report are closely connected to WP3, WP4, and WP5, and are also discussed with stakeholders in each living lab as part of WP1.

Among the information that can be found in the present report we can highlight:

- the main climate hazards that the research will focus on
- existing climate and weather data
- regional climate models, urban models, damage cost models and flooding models employed at WP2, WP3 and WP4
- existing observation datasets that can be used for model evaluation
- domains of interest for the CSAs
- periods of interest for event-based analyses and scenarios (2030-2035, up to 2050) to be downscaled
- lists of variables needed for urban modelling analysis, indicators calculation (T2.4) and to feed other models (developed in T2.3 or WP3/WP4)
- lists of required indicators that are used for impact assessments

- spatial resolution(s) of the downscaled data to be used at the CSAs
- analysis of hazards, extreme events and combined stress occurrence, magnitude (as event cumulative intensity), duration, and their spatio-temporal variability
- list of hazard indicators
- list of disaster risk indicators
- report on the work done in relevant projects

The information contained in this modelling framework are aligned with those contained in the experimental protocol (developed in Task 2.2) that operatively defined the strategies adopted for the statistical and dynamical downscaling activities over the CSAs. Furthermore, the existing climate and weather data reported in this modelling framework as well as in the “Catalogue of existing high resolution climate datasets” in Milestone MS20 of the CARMINE project represent the state of the art of climate information at km-scale currently available over the CSAs.

2. Overview of the CARMINE CSAs

The eight CSAs are described below with respect to their characteristics regarding their location, geographical situation, their specifics and risks related to natural hazards, as those were provided by the local CSA partners and extensive desk work. A broad selection of proposed indices is also provided to assess the hazards and their impacts in each CSA separately. Information from the Living Lab workshops (Deliverable 1.2) in each CSA is introduced at a later stage, together with the analysis of the hazards.

2.1 CSA Prague (CZ)

The Prague Metropolitan Area is located on a plateau intersected by the Vltava River valley. It spans approximately 4,822 km², with elevations ranging from 500 m above sea level on the plateau's highest hills to 154 m above sea level at the valley bottom. Prague, the largest city in the Czech Republic, has a population of around 1.3 million residents. The land cover of the region features a significant proportion of artificial surfaces, including urban fabric, industrial, commercial, and transportation areas, intermixed with arable land.

Prague metropolitan area is characterized by a moderately continental climate, with cold winters and mild to pleasantly warm summers. Average winter temperatures are around -1 °C, while summer maximums reach approximately 18.7 °C. Annual precipitation averages 525 mm, with the highest rainfall occurring from May to August and a winter minimum, often in the form of snow. Key sustainability and resilience challenges stem from ongoing suburbanization, intensive agriculture, and increasing traffic related to daily commuting and international transport. Public health is particularly vulnerable to climate risks, notably the growing frequency and intensity of heatwaves in Central Europe. Over the past two decades, heatwaves have been linked to increased heat-related mortality in Prague (Urban et al. 2022). Climate projections suggest that Central Europe will continue to experience substantial warming, especially in terms of maximum heatwave temperatures (Guerreiro et al. 2018). When combined with air pollution from heavy

traffic, extreme heat presents significant public health challenges, underscoring the need for robust local adaptation strategies.



Figure 1: Location of the Prague Metropolitan Area (red border)

2.1.1 Climate Hazards and Impacts

In Prague, the effects of climate change are already apparent, with rising temperatures, a more pronounced urban heat island effect, and increasingly frequent heatwaves. These trends are expected to intensify under future climate scenarios. While annual precipitation is projected to remain stable, seasonal patterns will shift toward wetter winters and drier summers. Heavy precipitation events are likely to become more extreme, accompanied by greater fluctuations in humidity. Additionally, air pollution contributes to ‘smog’ episodes, particularly during heatwaves. These combined hazards have led to increased mortality and morbidity and a decline in overall well-being. Impacts are commonly expressed as thermal (dis)comfort, urban overheating, or smog events synoptic situations marked by very poor air quality due to particulate matter, pollen, sand, or tropospheric ozone. Concerns about thermal comfort and air quality have drawn the attention of local stakeholders, making these issues a central focus of the CARMINE project.

2.1.2 Indicators

Thermal and air quality indices are applied as key climate indicators for CSA Prague, namely air temperature, universal thermal climate index (UTCI) and various thermal comfort indices: (i) Air temperature is obtained directly through observation time series or downscaled future projections; (ii) UTCI indicates the feeling of the outdoor temperature for human beings. The calculation is based on 2m air temperature, 2m dew point temperature, wind speed at 10m, and mean radiant temperature, where the mean radiant temperature represents the uniform temperature of an

imaginary black enclosure that would produce the same net radiant heat exchange with a person as the real, non-uniform surrounding environment. Other considered thermal comfort indices relate skin temperature and sweat secretion and depict overall personal feeling toward thermal environment. For instance, the Predicted Mean Vote (PMV), which aims to predict the mean value of votes of a group of occupants on a seven-point thermal sensation scale, and the Predicted Percentage of Dissatisfied (PPD) that provides the percentage of people predicted to experience local discomfort. PMV is calculated using environmental variables (temperature, mean radiant temperature, wind speed and humidity), human metabolic rate and clothing insulation and is used to evaluate indoor comfort. The result is compared with the thermal equilibrium of individual human-being for comfort assessment. PMV and PPD are complementary, together they provide a more comprehensive picture of occupant comfort and reveal more individual differences (metabolism, clothing, etc.).

To represent the air quality of the CSA Prague, different air quality indicators are applied to different aspects of the severity during “smog” episodes. The Air Quality Index (AQI) shows the concentration of the three pollutants (nitrogen dioxide (NO_2), particulate matter and ozone (O_3)) in the air that are most hazardous to human health, as a total number. The concentration of each pollutant reveals detailed sources of the air pollution, such as sulphur dioxide (SO_2), NO_2 , suspended particulates smaller than 10 μm in diameter (PM_{10}), suspended particulates smaller than 2.5 μm in diameter ($\text{PM}_{2.5}$), carbon monoxide (CO), and O_3 . More vulnerability indices could further be calculated to quantify the socio-economic impact of air pollutions.

2.1.3 Current Available Tools and Models

Climate models simulate weather and urban micro-climate within CSA Prague. Three different climate models are used for weather variation and spatial distribution of heat and air pollution for Prague: WRF (Weather Research and Forecast), COSMO-CLM (COSMO in Climate Mode) and the PALM Model System.

WRF is a numerical weather model for atmospheric research and forecasting developed in the United States since 1990s. The model is capable for both real-data simulations (e.g. ERA5, NCEP analysis, AgERA5, etc.) and idealized simulations. It is a flexible and efficient model which is suitable for applications from large eddy to global scales on high performance computing platforms. Driven by its communities, the model is widely used by various national centres and research institutions, incorporated with advancements in physics, numerics and data assimilation. For Prague CSA, it is used for event-based and long-term simulations.

COSMO-CLM is a non-hydrostatic regional weather and climate model, developed by CLM-community. It is used for weather forecasting (COSMO version developed by DWD) and regional climate simulations, with a resolution of 1 – 50 km and timescales up to multiple centuries. For Prague CSA, the regional climate model COSMO-CLM is used for downscaling, and its present time simulations are forced with daily ERA5 reanalysis data.

The PALM model system is a meteorological modelling tool for simulating atmospheric and boundary layer flows. The system is capable to resolve turbulence structures using large-eddy simulations (LES), adapted to HPC architectures. For coarser simulations, it supports the usage

of Reynolds averaged Navier-Stokes (RANS) for turbulence parameterisation. For urban climate applications with meso- or microscale, PALM can resolve buildings with their boundary-layer dynamics, thus calculates urban canopy modelling for heatwaves and pollutant dispersion.

Besides PALM, other air quality models like Copernicus Atmosphere Monitoring Service (CAMS) and the GRAL model are also implemented for Prague CSA. CAMS monitors global atmospheric composition of global air quality, greenhouse gases, aerosols and provides high-resolution multi-model ensemble forecasts of European air quality. CAMS also offers products of solar radiation and greenhouse gases and other anthropogenic emissions. Thus, it plays an active role in environmental monitoring, climate change mitigation, public health protection and support on the environmental regulations for policy makers. Further, the GRAL model system is an open-source high-resolution dispersion model for air quality assessment, developed by Graz University of Technology (TU Graz). The model can handle complex terrain and urban settings and outperforms other models especially at low-wind-speed conditions.

Epidemiological models are also employed to assess the impact of climate hazards on health such as heat-related mortality and morbidity in Prague. Risk evaluations draw on temperature-related mortality and morbidity data, utilizing daily death counts from all 22 Prague districts between 2001 and 2020. Individual risk assessment is further supported by analysis of emergency callouts in the City of Prague from 2014 to 2023, incorporating information on sex, age, timing, location, and the causes for ambulance dispatch.

2.1.4 Data Availability and Gaps

The available observational and modelled data provide a comprehensive foundation for urban climate analysis in Prague. This includes detailed simulations of summer climate indices projected to 2100, outputs from urbanized regional Weather Research and Forecasting (WRF) models in both operational and research configurations, and vulnerability assessments focused on heat exposure. These resources are complemented by meteorological forecasts and high-resolution (2.3 km) reanalyses from the Czech Hydrometeorological Institute's ALADIN model. Air quality is assessed using the ATEM Gaussian dispersion model, with ground-truth validation from standard meteorological observations collected at multiple sites throughout the city. While no explicit data gaps have been identified, areas for further improvement include the collection of finer-scale urban microclimate measurements (such as street-level thermal comfort indices), enhanced validation of air quality simulations with empirical pollution data, integration of socio-environmental datasets (for example, health records during heatwaves), and long-term consistency checks of observational records. The existing dataset is robust for climate modelling and heat risk assessment, but incorporating crowdsourced weather data or additional urban canopy parameters could further enhance its resolution and applicability.

2.1.5 Expectations from WP2 Modelling

Urban climate modelling plays a crucial role in understanding and mitigating future climate risks, particularly in the context of rising temperatures and increasing heat stress. This study focuses on a high-resolution spatial domain (Latitude: 49.9287° N – 50.1797° N; Longitude: 14.2107° E – 14.7210° E) to assess microclimate variability and urban thermal conditions under near-future

(2020–2050) and extended (up to 2100) climate scenarios. Key meteorological variables, including potential temperature, relative humidity, wind speed, and mean radiant temperature, will be simulated to evaluate thermal comfort and heat stress using indices such as the UTCI. Additionally, air quality interactions may be considered to provide a comprehensive assessment of urban liveability. The findings will support climate adaptation strategies by identifying high-risk zones and informing resilience planning in the face of escalating heat extremes.

2.1.6 *Specific Events to Model*

The heatwaves of 2015, 2018, and 2019 were primarily driven by persistent high-pressure systems, soil moisture deficits, and the advection of hot air masses. These events resulted in elevated health risks, increased agricultural stress, and higher energy demand. During winter, strong temperature inversions frequently developed under calm, high-pressure conditions, trapping cold air and pollutants near the surface. Modelling these events provides valuable insights into their underlying causes and impacts.

2.2 *CSA Leipzig (DE)*

Leipzig is located in central Germany, within the state of Saxony, along the White Elster River. The Leipzig Metropolitan Area, part of the “Sachsendreieck,” comprises a mix of urban and rural landscapes. Leipzig serves as the core city, surrounded by smaller towns and villages across mostly flat terrain, with rolling hills to the south and west. The area is further distinguished by a lake district created from former lignite opencast mines. The metropolitan area has a population exceeding 1.1 million, making it one of Germany’s largest. The regional climate features cold winters and warm summers, with an average annual temperature around 10 °C. The landscape is dominated by agricultural land interspersed with vast forested areas, such as the Leipzig Riverside Forest (Auwald) and the Dübener Heide Nature Park.

2.2.1 *Climate Hazards and Impacts*

The Leipzig Metropolitan Area faces significant climate hazards, including wildfires, heatwaves, and flooding each posing distinct threats to economic stability, urban infrastructure and broadly to the quality of life in the area. Addressing these challenges requires an integrated approach that combines mitigation, adaptation, and resilience-building strategies.

Wildfires contribute to air pollution and elevated public health risks, threaten energy infrastructure and cultural heritage, and diminish the city’s liveability and economic appeal. To mitigate wildfire risks, local authorities are expanding the urban greenbelt to create fire-resistant landscapes and strengthening building codes, particularly near forested areas. CARMINE modelling will support these efforts by informing planning, enhancing early warning systems, and increasing public awareness.

Heatwaves decrease labour productivity, drive up energy consumption for cooling, increase retrofitting costs, and result in more health emergencies. Local responses include expanding green and blue infrastructure such as urban parks, green roofs, water features, and reflective surfaces to reduce urban heat island effects. Building designs are being improved to enhance indoor comfort through passive cooling, shading, and ventilation. Public infrastructure adaptations

include heat action plans with additional cooling centres, adjusted work hours, and improved ventilation during extreme heat.

Flooding can damage infrastructure, cause costly repairs, disrupt the economy, and lead to long-term water scarcity and higher insurance and recovery costs. NBS, such as wetland restoration and permeable pavements, alongside upgrades to urban drainage systems, are being considered to increase flood resilience and adapt land use for better risk management.

2.2.2 Indicators

For the Leipzig CSA, a range of hazard indicators is employed to assess wildfire, heatwave, and flood risks. Wildfire indicators include extreme wind speed, soil dryness, heatwave duration, and drought incidence. Extreme wind speeds accelerate fire spread, while soil dryness increases flammability. Prolonged heatwave duration can act as a trigger for wildfires, and drought incidence highlights periods of insufficient rainfall that further elevate fire risk. For heatwaves, key indicators are temperature extremes and heatwave length, which quantify both the intensity and duration of these events. The seasonal warming trend is also monitored to capture the long-term influence of global warming. Flood hazards are primarily assessed by analysing the frequency, duration, and intensity of heavy rainfall events, as these factors are critical in determining flood risk.

2.2.3 Current Available Tools

Leipzig employs a suite of modelling tools tailored for climate and hazard management. WRF-ARW is used for meteorological and climate modelling, providing essential atmospheric data to downstream models such as LISFLOOD for hydrological and flood risk assessment and the NOA/BEYOND ML model for wildfire risk detection and prediction. Driven by ERA5 reanalysis, WRF-ARW delivers meteorological forcing over Leipzig at a 6-km grid resolution, or at finer scales if higher-resolution forecasts are available. LISFLOOD uses meteorological forcing at various temporal horizons to produce detailed flood risk assessments at a 1-arcminute resolution. The NOA/BEYOND model, trained on over a decade of historical wildfire events, also incorporates meteorological forcing to generate daily wildfire predictions, categorizing results into five risk levels.

Further, similar projects could be referenced for further applications. These projects include UrbanGreenEye, which focuses on thermal stress, hydrological relief, and flood monitoring; PREFERRED, which employs deep learning for wildfire prediction; and ASIMOV, which explores AI applications in fire detection and prevention. Additionally, the water-sensitive city development initiative rethinks urban water management through a “Sponge City” approach to optimize water flows and reduce sewage pressure. Lastly, CUT – digital twin involves developing urban data platforms and digital twins for cities and municipalities.

2.2.4 Data Availability and Gaps

The available data for wildfire risk assessment in the Leipzig region include WRF-ARW forecast outputs, fire risk modelling tools, and LISFLOOD simulations. However, significant gaps persist, particularly in the availability of historical wildfire burned area maps for Leipzig, Brandenburg, and Saxony, as well as ecological and ecosystem datasets. Furthermore, the absence of high-

resolution operational forecasts such as next-day fire risk predictions at 1–2 km grid scale limits the precision of local assessments.

2.2.5 *Expectations from WP2 Modelling*

The modelling work under WP2 will focus on assessing climate-related risks, including wildfires, heatwaves, and urban flooding. The spatial domain will be determined in collaboration with stakeholders.

The analysis will cover:

- Historical meteorological data (2014–2024) to establish baseline trends using the high resolution HYRAS datasets from DWD.
- Near future to mid-term scenarios (2020–2050) to project changes under different climate conditions.

Key variables include temperature, wind speed, precipitation, relative humidity, soil moisture, and fire indices. These will be used to derive risk indicators for wildfires (e.g., fire weather severity), heatwaves (e.g., duration and intensity), and floods (e.g., extreme rainfall events). Outputs will support evidence-based decision-making for adaptation and risk management.

2.2.6 *Specific Events to Model*

Specific wildfire, heatwave, and urban flooding events will be selected for modelling in close collaboration with stakeholders, focusing on high-impact cases that align with both stakeholder priorities and research objectives. Urban flooding events with significant consequences will also be prioritized in the modelling efforts.

2.3 *CSA Funen-Odense (DK)*

Odense, the largest city in the Metropolitan Area of the Funen Island, is Denmark's third-largest city, with a population of approximately 180,000 inhabitants. The city features a mix of residential, service, and industrial areas concentrated in the centre, surrounded by parks, agricultural land, small forests, and other natural environments. Odense is also home to historical and cultural landmarks, including churches and the birthplace of Hans Christian Andersen.

Situated at the bottom of Odense Fjord, where the Odense River flows, the area faces significant risks from coastal flooding and cloudbursts. Compound events, including storm surges, heavy rainfall, and local stream flooding, could exacerbate these hazards. The broader Funen Metropolitan Area includes numerous small and medium-sized coastal cities, many of which are low-lying and already exposed to coastal flooding during storm surges. Vulnerable sites, such as historic industrial harbour areas, face recurring flood risks, threatening protected buildings of high cultural and historical value.

2.3.1 *Climate Hazards and Impacts*

The Funen-Odense CSA focuses on flooding hazards driven by storm surges associated with extratropical cyclones which produce abundant rainfall, with considerable winds and storm surge associated. The floods damages infrastructures like buildings, roads and utilities, disrupts transport and causes power outages due to flooded substations. They also lead to economic

losses, higher insurance claims and increased recovery costs. Moreover, social disruptions could also happen either during the evacuation and displacement of residents or the corresponding health risks from contaminated floodwater. The floods also erode coastal and riverine areas, triggering saltwater intruding into freshwater systems.

2.3.2 *Climate Indicators*

Various flood indicators describe the severity of floods, including Elevation, slope, maximum storm surge height, duration of high-water levels, maximum wind speed, and storm direction. Low-lying coastal and inland areas identified with elevation are most vulnerable to inundation. Flatter areas (low slope) provide poor drainage tend to have prolonged flooding while steep areas (high slope) are likely to have faster runoff but potential for flash floods and erosions. Maximum storm surge height determines the costal inundation extent. Duration of high-water levels show the efficiency of the drainage responses. Maximum wind speed determines wave setup by increasing surge height. Nevertheless, storm direction affects rainfall distributions.

2.3.3 *Current Available Tools*

The integration of climate models, flood tools and observational data in CSA Odense provides a robust framework for assessing flood risks under current and future climate scenarios. For climate modelling and storm surge analysis, the Joint Research Centre (JRC) provides a European-scale dataset of extreme storm surge levels (ESSL), derived from downscaled CMIP5 global climate models using the Delft3D-FLOW hydrodynamic model at 0.2° resolution. This dataset covers both historical (1969–2004) and projected periods under RCP4.5 and RCP8.5 scenarios (2009–2099). In addition, various flood models are utilized to assess flood risks and evaluate economic impacts, including the DTU Damage Cost Model, SCALGO Live, KAMP, and Kystplanlægger. The DTU model offers high-resolution flood risk assessments, incorporating land use, environmental, and socio-economic factors to estimate damages across sectors such as residential and industrial buildings, transport infrastructure, health, recreation, and tourism. SCALGO Live provides digital solutions for surface water management in urban areas, supporting nature restoration, municipal planning, and infrastructure development. KAMP is a powerful tool for assessing and visualizing climate-related risks, especially flooding, with a focus on infrastructure and property impacts. Kystplanlægger, launched by the Danish government in 2017, integrates data-driven risk assessments and practical solutions to help municipalities, landowners, and policymakers address future flooding, coastal erosion, and climate change impacts through sustainable, proactive measures.

For the Funen-Odense CSA, observational data used for validation include water level measurements, reanalysis datasets, gridded observation products, and crowd-sourced flood data. Water level data are collected from multiple ports across different municipalities on Funen. The ERA5-Land dataset provides comprehensive meteorological, land surface, and energy budget variables from 1950 to the present. The CERRA reanalysis product adds further atmospheric variables across multiple layers, offering both historical modelling and short-term forecasts. Gridded observational datasets, such as EMO-1 (Gomes et al., 2025; at ~1.8 km resolution) and E-OBS (at 12 km resolution), supply high-quality ground truth for model calibration

and validation. Additionally, event-specific studies are supported by incorporating crowd-sourced flood data.

2.3.4 Data Availability and Gaps

Available data includes historical storm surge and wind observations, reanalysis datasets, and flood simulation tools. However, there are notable gaps in wind speed and direction data for extreme events, both in historical records and in near- and long-term projections over Denmark. In addition, future sea level rise projections for Danish inland waters are particularly needed for mid-century (2041–2070) and end-century (2071–2100) under the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios.

2.3.5 Expectations from WP2 Modelling

The WP2 modelling will focus on the spatial domains of Odense (Latitude 55.3244° N–55.4506° N; Longitude 10.3104° E–10.4721° E) and Svendborg (Latitude 55.0415° N–55.0836° N; Longitude 10.561° E–10.6596° E). The analysis will target mid-century (2041–2070) and end-century (2071–2100) periods under the SSP1-2.6, SSP2-4.5, and SSP3-7.0 climate scenarios. Key variables include hourly eastward and northward near-surface wind components, as well as near-surface wind speed. Particularly important are indicators of changes in windstorm intensity and frequency, such as maximum daily or sub-daily wind speeds, which are essential for assessing climate impacts in Denmark.

2.3.6 Specific Events to Model

Storm surge affecting southern parts of Denmark (October 21, 2023), and storm surges that hit northern part including Odense (November 1-2, 2006, and December 2013).

2.4 CSA Athens (EL)

The Athens Metropolitan Area (Figure 2) features complex topography, surrounded by the Parnitha (1,413 m), Penteli (1,109 m), Hymettus (1,026 m), and Egaleo (469 m) mountains, alongside a 25 km-long coastline to the south. The continuous Athens Urban Area includes the Athens Centre, Piraeus, and parts of East and West Attica, with a population exceeding 3.7 million. The city hosts globally significant cultural heritage monuments and attracts over 6 million tourists annually. Athens has a typical Mediterranean climate, with mild winters and dry, hot summers often marked by heatwaves. Local sea-breeze and regional wind patterns, such as the Etesian winds, influence the city's ventilation properties. These complexities underscore the need for high-resolution observations and modelling to understand local atmospheric dynamics.



Figure 2: Location of the Athens Metropolitan Area

2.4.1 Climate Hazards and Impacts

The Athens Metropolitan Area is primarily affected by extreme heat and heatwaves.

- Heatwaves: Extended periods of high temperatures impacting human mortality, especially among vulnerable populations, energy demand, and urban heat stress.

2.4.2 Indicators

The analysis of extreme heat in Athens incorporates mostly temperature-based and precipitation indicators, due to the heat hazard focus for Athens. Temperature-based metrics include hot days ($T_{max} > 90$ th percentile) measuring high daytime temperatures, hot nights ($T_{min} > 90$ th percentile) indicating nighttime heat stress, and tropical nights ($T_{min} > 20^{\circ}\text{C}$) reflecting prolonged heat discomfort. Heat wave duration (≥ 5 consecutive days with $T_{max} > 90$ th percentile) assesses persistent extreme heat, while extreme maximum temperature records peak values and thermal amplitude ($T_{max}-T_{min}$) evaluate heat stress intensity. Cooling Degree Days (sum of daily $T_{mean} - 18^{\circ}\text{C}$) estimate cooling energy needs. Drought indicators track dry days (precipitation $< 1\text{mm}$), maximum consecutive dry days (intensifying heat impacts), and contrast with rainfall days ($P > 1\text{mm}$) and maximum 5-day rainfall. Wind indicators examine how minimum/maximum speeds affect heat islands or storm potential.

2.4.3 Current Available Tools

The current available tools include the WRF-ARW model at 1 km resolution, coupled with an Urban Canopy Model (Spyrou et al., 2024; Skamarock et al., 2019) to simulate urban heat and land-atmosphere interactions, under the complex topographic variability of the area. The BEP/BEM parameterization will be used (Building Effect Parameterization and Building Energy Model; Martilli, et al., 2002; Salamanca et al., 2010).

Observational data consists mainly of METAR reports from the airport, in-situ measurements from the Hellenic National Hydrological and Meteorological Service, ERA5-Land and CERRA reanalysis datasets, as well as crowdsourced data.

2.4.4 Data Availability and Gaps

The available data include high-resolution operational simulations and heatwave observations, as mentioned above, with no identified data gaps.

2.4.5 Expectations from WP2 Modelling

The WP2 modelling will focus on the Athens Metropolitan Area (Figure 2), covering historical periods (1970–present) and future projections under RCP8.5 scenarios, including selected intense heatwave cases for testing NBS deployment. Key variables include daily air temperature at 2m (mean, min, max), relative humidity, skin temperature (mean, min, max), u and v wind components at 10m (mean, min, max), and total precipitation. The NBS that will be deployed will include typical interventions for urban areas, such as green roofs (Spyrou et al., 2024)

2.4.6 Specific Events to Model

August 2021 and July 2023 heatwaves, with a focus on assessing the impact of NBS like green roofs and urban cooling strategies.

2.5 CSA Barcelona (ES)

Barcelona, situated on the Mediterranean coast, is the heart of a metropolitan area with a population of over 5 million. The city is located on a plain bordered by the Besós River to the north, the Llobregat River to the south, and the Tibidabo mountains to the west. Barcelona features a dense urban core encircled by an extensive industrial belt.

Renowned for its rich history, iconic architecture, and vibrant beaches, Barcelona is also a thriving hub for technology businesses, thanks to its strategic location, modern infrastructure, and highly skilled workforce. The city enjoys a Mediterranean climate, characterized by mild, wet winters (average temperature around 13 °C) and hot, dry summers (average temperature around 26 °C), with annual rainfall averaging 566 mm.

2.5.1 Climate Hazards and Impacts

The Barcelona Metropolitan Area faces multiple interconnected hazards, including heatwaves, wildfires, and droughts. These hazards exacerbate socio-economic vulnerabilities and affect human health, infrastructure, and environmental quality:

- Heatwaves: Extended periods of high temperatures impacting human mortality, energy demand, and urban heat stress.
- Wildfires: Risk driven by drought, heatwaves, and vegetation accumulation, leading to air pollution, carbon emissions, and infrastructure damage.
- Drought: Persistent dry conditions threatening water availability, agricultural productivity, and urban water supplies.

2.5.2 Indicators

- Heatwave indicators: Maximum daily temperatures, heatwave duration.

- Drought indicators: Consecutive dry days, Standardized Precipitation Index (SPI), SPEI.
- Wildfire indicators: Fire Weather Index (FWI), fire danger indicators (e.g., days in a year with high FWI), fire ignition probability, fire susceptibility.

2.5.3 *Current Available Tools*

- Climate models: CMIP6 global climate simulations bias corrected and downscaled with statistical methods, with further urban-scale refinement using advanced machine learning techniques.
- Wildfire models:
 - a) Fire ignition probability model
 - b) Fire susceptibility model
- Observational data:
 - a) EMO-1 climate variables
 - b) Chelsa climate variables
 - c) Elevation – Eurostat
 - d) NDVI from Modis version 6
 - e) Corine land cover 2018
 - f) EFFIS Copernicus

2.5.4 *Data Availability and Gaps*

- 1) Available data: High-resolution climate data, wildfire risk maps, and drought indices.
- 2) Data gaps:
 - a) Projections of drought duration and severity.
 - b) Historical burned area maps and fire intensity data.

2.5.5 *Expectations from WP2 Modelling*

- 1) Spatial domain: Latitude: 40.5200° N - 42.7031° N; Longitude: 0.1500° E - 3.3500° E.
- 2) Target periods: Near-term (2025-2050). Scenarios of interest are: SSP1-2.6, SSP2-4.5 SSP5-8.5.
- 3) Variables: Maximum and minimum temperature, precipitation, near-surface relative humidity, u and v horizontal wind components, at a daily timescale. Soil moisture at 6 hr intervals.
- 4) Indicators: maximum daily temperature, heatwave length, FWI, SPI, SPEI, and consecutive dry days.
- 5) Indicators for the wildfire risk index are related to hazards (high temperatures, relative humidity, fuel moisture, fuel load, wind speed and direction), exposure (number of vulnerable elements exposed to wildfire risk such as the number of communities within less than 500

meters of forest or with critical infrastructure, etc.), and vulnerability (profile of communities such as elderly people, foreigners, economic capacity, etc.)

2.5.6 *Specific Events to Model*

- 1 August 1994 wildfire in Collserola, which significantly threatened urban communities.
- 2 Notable wildfires events affecting Barcelona in the past.

2.6 *CSA Bologna (IT)*

Bologna, situated in the Po Valley, has a population of 400,000 inhabitants within the city and one million in the broader metropolitan area. The region frequently experiences heatwaves, posing particular challenges for its aging population, currently, 37% of families in Bologna include at least one elderly member, and individuals over 80 years old comprise 8.6% of the metropolitan population (9.3% within the city itself). The urban landscape of Bologna reflects its historical development, with a dense city structure shaped by growth from the Medieval period through the 19th and early 20th centuries. While local urban planning initiatives have focused on microclimate studies and regulatory measures, future challenges, including more intense heatwaves and the urban heat island effect, remain significant concerns for the city's resilience and well-being.

2.6.1 *Climate Hazards and Impacts*

The Bologna Metropolitan Area faces significant climate hazards, including heatwaves, the urban heat island (UHI) effect, air pollution, and multi-hazard conditions. Cities are particularly vulnerable to heatwaves and extreme temperatures due to the UHI effect, which places urban residents at a higher risk from the adverse effects of rising temperatures compared to rural communities. Heatwaves intensify in urban settings as paved ground absorbs heat, buildings and narrow streets trap hot air, and human activities further increase the surrounding temperature. This leads to heat stress, which can cause various health issues, has an impact on general human well-being and has been linked to a rise in morbidity, posing an especially severe threat to Europe's aging population (ECMWF, 2024b). The exacerbation of local heating effects can also reduce thermal comfort and impact energy consumption. As for the multi-hazard conditions, the combined effects of heatwaves and poor air quality create compounded risks for human health.

2.6.2 *Indicators*

- 1 Heatwave indicators: Maximum summer temperature, average annual temperature, and tropical summer nights ($T_{min} \geq 20^\circ\text{C}$), annual cumulative precipitation, and intensity and duration of heatwaves.
- 2 UHI indicators:
 - a) Urban Heatwave Thermal Index (UHTI). This index is used to quantify daytime air temperature variability patterns in an urban environment during a heatwave. UHTI is a reliable representation of thermal criticalities in the metropolitan area for its inhabitants.

- b) PET (Physiological Equivalent Temperature) and PMV (Predicted Mean Vote) values.
- 3 Air quality indicators: general air quality indices.
- 4 Multi-hazard indicators: Risk indices for combined heatwave-energy consumption impacts. For example, the cooling degree days (CDD), which is defined as the number of degrees that a day's average temperature is above 18 °C. The number of days on which the CDD is greater than 5 indicates days with a high demand for electricity for cooling.

2.6.3 *Current Available Tools*

- Climate models:
 - a) COSMO-CLM and ICON-CLM: Regional models providing high-resolution projections of temperature and precipitation, among other variables.
 - b) ENVI-met: An integrated 3D modelling software for urban microclimate and climate adaptation strategies.
 - c) CLIMPACT2: An R software used to calculate climate extremes indices from weather data (usually stations).
- Decision support tools: UrbanProof Toolkit, which is a decision support system aimed at enabling more informed decision-making for climate change adaptation planning.
- Observational data:
 - a) Satellite data, Eraclito Database, and regional environmental agency ARPAE pollution data.
 - b) High-resolution UHTI maps for urban heatwave impacts and the deprivation index for health conditions for population categories.

2.6.4 *Data Availability and Gaps*

- Available data: High-resolution climate models, observational data, and decision support tools.
- Data gaps: Fine-scale projections for UHI under future climate scenarios.

2.6.5 *Expectations from WP2 Modelling*

- Spatial domain: Latitude: 44.25° N - 44.36° N; Longitude: 11.12° E - 11.29° E, covering the entire Bologna Metropolitan Area, which is centred at 44° 29' 38" N 11° 20' 34" E.
- Target periods: Mid-century (2030-2050) and potentially end-century (2070).
- Variables: Temperature, precipitation, humidity, wind speed, air quality indices. An expected outcome of the CSA Bologna will be an air quality index for the metropolitan area (AQI).
- Indicators: UHI indicators such as UHTI, PET, and PMV.

2.6.6 Specific Events to Model

- Heatwaves during July 2024, with a focus on the UHI effect and public health impacts.
- Continuous time series analysing UHI and heatwave coupling.

2.7 CSA Brasov (RO)

Brasov is located at the contact between the Eastern and Southern Carpathians, including 17 Local Administrative Units (LAUs) with a population exceeding 400,000 inhabitants. The region spans 1,640 km² (Figure 3, with data from [OpenStreetMap](#); [CORINE Land Cover 2018](#); [European Union's Copernicus Land Monitoring Service information](#); [National Agency for Cadastre and Land Registration of Romania](#)). The Brasov Metropolitan Area (BVMA) is in a mountain region dominated by forests, including natural protected areas, with agricultural areas and expanding urban lands in the hydrographic basin areas. The BVMA is a regional economic hub, facilitating the connection between the western, central, eastern and southern parts of Romania. It is also an important touristic region based on natural and cultural heritage, offering both summer and winter activities. The region experiences active urbanization processes, dominated by urban expansion, including the reconversion of former industrial areas to residential, office, and commercial), and development of transport infrastructures.

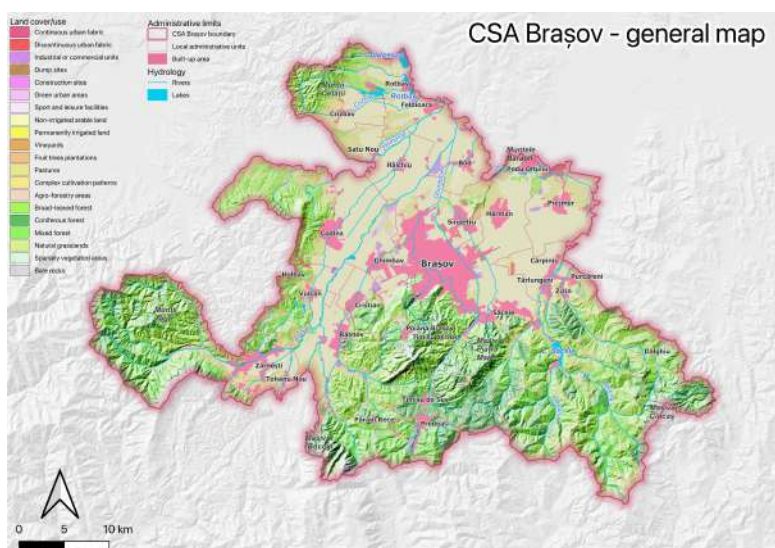


Figure 3: Physical Map of the Brasov Metropolitan Area

The climate of Brasov is continental, with cold winters when temperatures often drop below -5 °C, and warm summers, with average highs around 25 °C. In current climate, the region is increasingly affected by shifts in temperature patterns and precipitation distribution, which increase its vulnerability to climate-related hazards such as heat waves, floods, and droughts. These changes contribute to amplification of water scarcity, which in the long term could potentially impact domestic water supply, economic activities, and the health of local ecosystems. Although Brasov has developed environmental action plans, including a climate adaptation strategy, the implementation of concrete measures remains limited.

2.7.1 Climate Hazards and Impacts

Brasov is particularly exposed to climate hazards such as water scarcity (i.e., drought from all its perspectives - meteorological, hydrological, pedological, ecological and socio-economic), flash floods and heatwaves. These hazards have direct implications for the development of urban areas (urbanization), human and ecosystem health, and tourism activities.

Key climate hazards and their impacts include:

- **Water scarcity:** The region experiences meteorological, hydrological, and socioeconomic drought phenomena that lead to water scarcity, which impacts drinking water availability, winter tourism (through snow scarcity translated in reduced snow cover and artificial snow making constraints), agriculture and ecosystem services.
- **Flooding/flash flooding:** Short-duration, high-intensity precipitation events often lead to flooding and damages to transport infrastructure disrupting mobility, buildings, and agricultural lands.
- **Heatwaves:** The increasing frequency and severity of heatwaves amplify the bioclimatic thermal discomfort and heat-health risks particularly in vulnerable population groups. These extreme events also heighten the pressure on energy systems due to rising energy demand for cooling and accelerate of snowmelt processes, contributing to the shortening of ski tourism season.

2.7.2 Indicators

This case study uses a range of hazard indicators tailored to the specific hydrometeorological extremes affecting the BVMA. The list of hazard indicators include:

- **Water scarcity:**
 - **Drought:** Maximum number of consecutive dry days (< 1 mm), SPEI, Water Exploitation Index+ (WEI+), water demand/supply balance for human activities.
 - **Snow scarcity:** Number of days suitable for artificial snowmaking (average air temperature < -3 °C), number of days with snow cover ≥ 30 cm (natural ski conditions) and “white winter” days (snow depth ≥ 5 cm).
- **Flooding/flash flooding:** Number of days with very heavy precipitation (≥ 20 mm), maximum number of consecutive wet days (≥ 1 mm), the greatest 1-day precipitation (Rx1day), number of flood/flash flood events, flood extent, duration of water retention after flooding.
- **Heatwaves:** Number of summer days (maximum air temperature ≥ 25 °C), number of very hot days (maximum air temperature ≥ 35 °C), number of tropical nights (minimum air temperature ≥ 20 °C), Universal Thermal Climate Index (UTCI)/Physiological Equivalent Temperature (PET) for evaluating the bioclimatic thermal discomfort, urban heat island intensity (UHI), sky view factor (SVF).

Important factors to be considered, besides climatological factors, are the terrain topography and the development of the urban areas.

2.7.3 Current Available Tools

- **Climate models:** WRF and ICON-CLM for regional/urban climate simulations; PALM-4U for urban-scale climate simulations of heatwaves and UHI.
- **Risk assessment tools:** Water availability scenarios in the Tărlung-Săcele reservoir (primary water source for BVMA, according to Tudose et al., 2022) (Figure 4); urban master plans with integrated heatwave risk assessment.
- **Observational data:**
 - a) Air temperature and precipitation data from local weather stations.
 - b) Water discharge data from the Tărlung River basin and reservoir.
 - c) Land cover data from the TopRO5 geospatial database

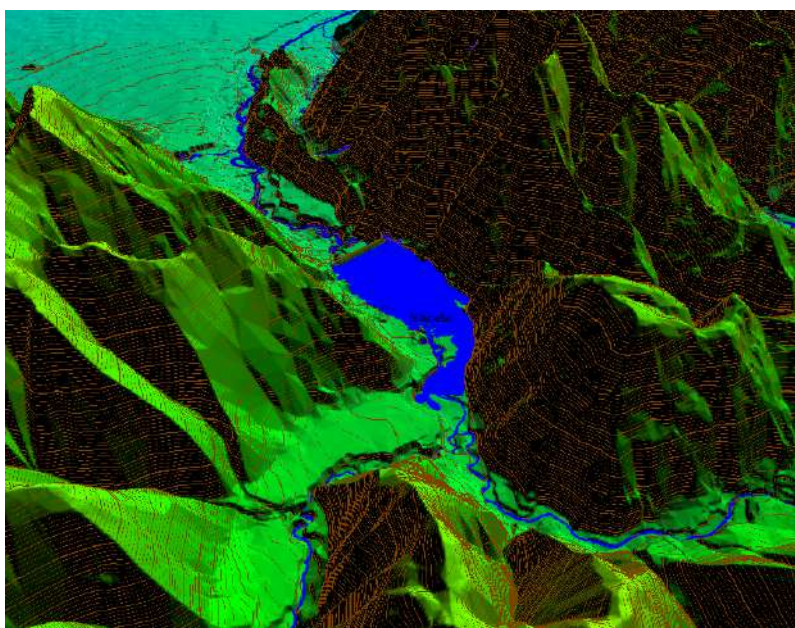


Figure 4: Tărlung river and Săcele reservoir.

2.7.4 Data Availability and Gaps

- Available data:
 - a) Topographic and flood risk maps.
 - b) Demography dynamics.
 - d) Temperature and precipitation data (1981–2024).
 - c) Data about forest vegetation and composition.
 - d) Digital terrain model (DTM) at 2-5 m spatial resolution.

- e) Water discharge data from the Tarlung River basin and reservoir.
- f) Average, minimum and maximum monthly flows for 5 watercourses, the most important within the CSA (2004-2023)
- g) Land cover data from the TopRO5 geospatial database (Figure 5).

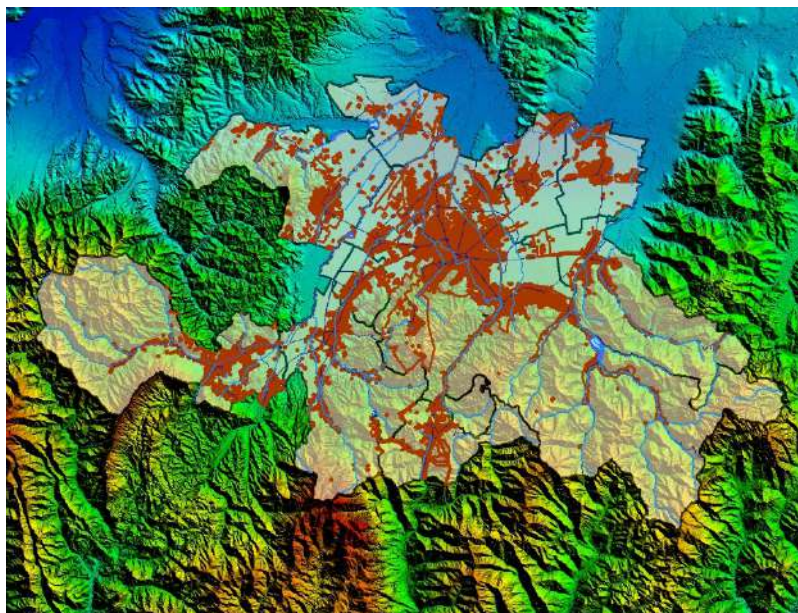


Figure 5: Geospatial National Database TopRO5 in Brasov metropolitan area.

- h) Data from 1992-2023 about resident population dynamics and data from 2010-2023 about touristic overnights.
 - i) Meteorological data associated with water related hazards includes temperature at soil level and at 2m, precipitation, solar radiation and wind speed and direction.
 - j) Agrometeorological indicators from 1979 to present derived from reanalysis (AgERA5).
 - k) The volume of water supplied to various consumers and the volume of water exploited by the APA Brasov Company, the main water supplier in the metropolitan area.
- Data gaps:
 - a) High-resolution snow cover projections under future climate scenarios.
 - b) Updated flood extent and damage assessments for flash flood events.
 - c) Fine-scale hazard and vulnerability mapping for heatwave-exposed populations.
 - d) Up-to-date digital surface models for heat-islands delimitation.

2.7.5 Expectations from WP2 Modelling

- Spatial domain: Latitude: 45.22° N - 45.53° N; Longitude: 25.09° E - 25.58° E.

- Target periods: Near-future (2020–2050) climate projections with historical baselines (2010–2020) and specific analyses (e.g., NBS) on the present climate (2018–2025).
- Variables: Air temperature, precipitation, snow cover (km-scale historical data and fine-scale climate projections for the near future from atmospheric and hydrological parameters). In addition, the CSA needs discharge rates in the Sacele reservoir and data regarding external inflow/outflow for BVMA, especially outflow of the Olt River tributaries. Flood frequency in the fine-scale climate projections.
- Indicators: see the *Indicators* subsection above.

2.7.6 Specific Events to Model

- **Water scarcity.** Specific periods of the worst winter seasons related to snow cover scarcity in the last 10 years (to be identified by the CSA) will be investigated, based on the analysis of temperatures, precipitation and snow cover during the identified periods.
- **Floods/flash flood events.** Between 27 and 30 June 2018, the Târlung River basin experienced a severe flash flood event, with cumulative precipitation reaching approximately 245 mm over four days (equivalent to nearly 30% of the basin's average annual rainfall). This extreme hydrological event caused significant damage to local infrastructure and led to a sharp increase in water turbidity. As a result, the treatment and distribution of drinking water became unfeasible for nearly two weeks. During this period, water supply was maintained through emergency groundwater extraction.

Another critical event to be modelled is the June 2023 flood, which caused widespread urban inundation and disruptions across Brasov.

In addition to modelling these events, areas with high flood risk will be reassessed using integrated geospatial and climate datasets.

Urban- and regional-scale modelling will also support the evaluation of NBS aimed at mitigating the impacts of urban heat island (UHI) and flash floods, while contributing to the protection and sustainable management of local water resources.

- **Heatwaves.** Two heatwave cases will be modelled, namely 22–24 July 2022 and 26–29 August 2023, with a focus on the fine-scale UHI description (spatial distribution, amplitude, evolution). Additionally, the impact of NBS for attenuating UHI will be investigated through urban-scale modelling.

2.8 CSA Birmingham (UK)

Birmingham, the UK's second-largest city, has a population of 1.1 million and a growing demographic characterized by youth: 36% of the population is under 25 years old. 51% of Birmingham's population are from Black, Asian or other minority ethnic groups (<https://cityobservatory.birmingham.gov.uk/p/analysis-of-census-2021-data/>). However, the city faces significant socioeconomic challenges, including housing shortages (40–50,000 homes

needed), high levels of socio-economic deprivation, with 43% of the population living in the 10% most deprived localities in England (<https://www.cqc.org.uk/care-services/local-authority-assessment-reports/birmingham-cc>), and ongoing financial problems within the City Council which was declared bankrupt in September 2023.

Environmental challenges include poor air quality, the urban heat island effect, and pluvial and fluvial flooding. Despite financial constraints, evidenced by the 2023 declaration of bankruptcy under a Section 114 notice, Birmingham remains committed to sustainability. The “Our Future City: Birmingham Framework 2040” outlines an inclusive, green vision for the city. Birmingham’s biophilic status (declared in 2014) and its designation as a Tree City of the World (since 2020) highlight its extensive green spaces, though their accessibility and quality remain uneven. The city’s Climate Risk and Vulnerability Assessment (CRVA) integrates environmental, physical, and socio-economic data to identify and address climate risks, making Birmingham a leader in urban climate resilience efforts.

2.8.1 *Climate Hazards and Impacts*

The Birmingham Metropolitan Area focuses on three key climate hazards: extreme rainfall events (pluvial flooding), extreme high temperatures, and climate seasonality and compound temperature-moisture changes.

Pluvial flooding is defined as “flooding which results from rainfall-generated overland flow, before the runoff enters any watercourse or sewer.” (WHO, 2024b). This type of flooding occurs when heavy rainfall overwhelms drainage systems and waterways and can lead to flooded buildings and disruptions to transportation infrastructure. Poor vegetation management can increase flood risk, as leaves and other debris block drains exacerbating flood risk.

CSA Birmingham will consider how to manage urban vegetation under a changing climate. To do so it requires information on heat extremes to understand how these are changing, and how these can impact trees and other vegetation in the city (e.g. tree species planting for the future, watering regimes), and how trees and other vegetation can cool the urban environment and act as a NBS for climate resilience. It is crucial to understand changing rainfall patterns to plan for (i) drought (and therefore tree watering), and (ii) pluvial flood risk, for trees and green infrastructure can alleviate flood risk, and the city is currently considering Natural Flood Management schemes in some city locations. Moreover, understanding tree phenology under a changing climate is important for vegetation management, for example to understand the relationship between leaf fall and heavy rainfall events that increases pluvial flood risk.

2.8.2 *Indicators*

- Pluvial flooding indicators:
 - a) Hourly rainfall (>10 mm/h and >30 mm/h).
 - b) Accumulated monthly precipitation above historical averages.
 - c) High monthly precipitation (>75th percentile), in mm/month.
- Extreme high temperature indicators:

- a) Number of warm nights ($T_{min} > 20\text{ }^{\circ}\text{C}$).
- b) Number of hot days ($T_{max} > 30\text{ }^{\circ}\text{C}$).
- c) Number of summer days ($T_{max} > 25\text{ }^{\circ}\text{C}$).
- d) Land surface temperature variations.
- Climate seasonality indicators:
 - a) Estimated leaf fall dates.
 - b) Accumulated degree days for key tree species.

2.8.3 *Current Available Tools*

- Climate models:
 - a) JULES (Joint UK Land Environment Simulator): Simulates land surface processes such as energy balance and hydrology.
 - b) Climate/earth system model ensembles, such as CMIP5 and EURO-CORDEX for assessing climate projections.
- Risk assessment tools:
 - a) Extreme rainfall events and associated pluvial flood risk are evaluated with maps and time series of extreme rainfall hazard indicators and the sensitivity between pluvial extremes and land surface characteristics, including varying tree cover scenarios across the region.
 - b) Maps and time series of different temperature indicators will assess risks regarding extreme warm temperature climate hazards and their relationships with varying tree cover scenarios.
 - c) The CRVA by the Birmingham City Council (Birmingham City Council, 2024) as well as tree data are core risk assessment tools for the evaluation of pluvial flooding and extreme heat risk.
- Observational data:
 - a) UK Met Office UKV weather forecast data (hourly/daily measurements) and HadUK-Grid daily 1km gridded UK data.
 - b) UK Environment Agency open GIS datasets for risk of flooding from surface and the extent of flooding from surface water that could result from a flood with a 3.3%, 1% and 0.1% chance in any given year.
 - c) Tree maps by the Birmingham TreePeople, Birmingham City Council tree inventory data and the UK National Tree Map.

2.8.4 *Data Availability and Gaps*

- Available data:

- a) Flood risk maps, historical and simulated climate data including temperature and precipitation data.
 - b) Tree inventory data and climate sensitivity thresholds for tree species.
- Data gaps:
 - a) Station (historical) observations are sparse across the area for model validation of extreme warm temperatures, extreme rainfall and pluvial floods.
 - b) For climate seasonality and compound temperature-moisture changes, base temperature and accumulated degree day thresholds for tree species, can provide an estimate of leaf seasonality but this is generic rather than species specific.
 - c) JULES has limited representation of the role of tree interception during rainfall events and changing phenology on leaf fall which are likely to influence pluvial flooding. For instance, localized flooding due to blocked drains was caused in 2022 due to drought conditions that lead to an unusually high number of trees losing their leaves in late summer, rather than autumn.

2.8.5 *Expectations from WP2 Modelling*

- Spatial domain: The West Midlands Combined Authority Area. Approximate coordinates: Longitude: 2.9° W - 1.2° W; Latitude: 52° N - 53° N.
- Target periods:
 - a) Historical baseline: 1991–2020.
 - b) Future projections: 2020–2050, potentially extending to 2070.
- Variables: Hourly and daily rainfall, temperatures (Tmax/Tmin), and leaf fall phenology estimates.
- Indicators:
 - a) Hazard maps for pluvial flooding and urban flood risks.
 - b) Heat stress and pluvial flood risk indicators (see above).
 - c) Leaf phenology metrics (e.g. the timing of leaf fall) to identify periods of increased pluvial flood risk.

2.8.6 *Specific Events to Model*

- Storm Doris in 2017: Economic analyses of the flooding impacts.
- Flash floods in 2023: Analysis of heavy rainfall events exceeding drainage capacity.
- Flash floods in September 2024: Analysis of short duration heavy rainfall events exceeding drainage capacity.
- Additionally, precipitation events with certain thresholds (mm/h) could be modelled.

- For assessing the influence of trees as NBS in the area, seasonality in leaf phenology can be modelled, as well as high-risk combined leaf fall and high precipitation events.

3. Climate hazards in the CARMINE CSAs, Indices and Impacts

Table summarises the climate hazards concerned by the CSAs, which were documented in the Living Labs (LLs) organised by WP1 and those recommended by the consortium partners in the CSAs. The results of Deliverable 1.2 by WP1 indicate that either extreme heat or heatwaves are a challenge in five CSAs. Funen-Odense deals with coastal and river flooding, while Birmingham is concerned with pluvial (rain-related) flooding. Barcelona considers the challenge of wildfires, and Brasov considers water scarcity. The local partners recommendations led to the inclusion of a few additional hazards beyond those identified in the LLs. Heat was also identified as a relevant hazard for Brasov, so that in total six CSAs consider extreme heat/heatwaves as their primary climate-related challenge and led to the respective analysis of heatwaves (see section 3.6 Heatwaves) being extended to all CSAs. In addition to Funen-Odense and Birmingham, Brasov and Leipzig are also considered in the analysis of hazards related to wet events (see section 3.8 Floods, Extreme Precipitation, Wet Events). Droughts are a selected hazard and investigated in Barcelona, Brasov, and Prague (see section 3.7 Droughts), with Prague being included in particular due to the city's aim to plant 1.5 million new trees around the city. For each of these climate hazards, researchers identified between 14 and 99 associated risks. The Birmingham LL workshop produced 99 risks over a range of sectors associated with extreme heat and pluvial flooding. Addressing the whole of 99 identified risks and their changes under different climate scenarios could not be covered by this Deliverable 2.1 and the project in total, Deliverable 1.2 recommends that the CSA leading partners should cross-check whether the modelling framework supports the general findings of the LL.

Table 1: Climate Hazards Concerned by CSAs

CSA	Climate Hazards
Prague	Extreme heat, air pollution
Leipzig	Extreme heat, wildfire, floods
Funen-Odense	Floods
Athens	Extreme heat
Barcelona	Extreme heat, wildfire, water scarcity
Bologna	Extreme heat, air pollution
Brasov	Water scarcity, floods, extreme heat
Birmingham	Extreme heat, pluvial flooding

Several risks emerging due to the above hazards overlap across the regions, including adverse health effects, rising energy demands, unequal access to cooling solutions, biodiversity loss, and water shortages. Shared economic concerns include reduced tourism, business disruptions, and

declining investment appeal. However, local factors, such as geography, economic conditions, governance systems, and social vulnerabilities, create distinct risks in each CSA.

3.1 Observational Data Set Across the CARMINE CSAs

A harmonised analysis of the hazards of concern for each CSA (Table) is undertaken based on the gridded observations data set EMO-1. The European Meteorological Observations (EMO-1) dataset is a high-resolution, gridded meteorological product developed under the Copernicus Emergency Management Service. It provides (sub-)daily data for variables such as precipitation, temperature, wind speed, solar radiation, and water vapour pressure based on quality-controlled ground station observations. The data are interpolated to grids using the Angular Distance Weighted method. The resolution of EMO-1 is 1 arcminute (approx. 1.8×1.8 km) for the period 1990–2023 (Gomes et al., 2025). Further, and in order to identify potential differences in observed trends related to the high spatial resolution of EMO-1, the calculation of the indices has also been based on the E-OBS v. 31.0e ensembles dataset at 0.1° regular grid (Cornes et al., 2018).

For a broader view of the areas surrounding the CSAs but also for downscaling purposes that require a larger amount of grid points, the analysis below is made with larger areas compared to those of the CSAs. Spatially aggregated figures refer to these greater areas.

3.2 Climate Indicators

The climate indicators used in this deliverable are presented here. The plethora of existing indicators in the literature are not covered here, while a selection of heat-related, drought/wetness indicators and an indicator that accounts for the combined impact of two hazards are selected and presented in this section.

A comprehensive list of climate-specific indices, inclusive a couple with novel developments, that focuses on individual types of natural hazards, such as floods, droughts, or heatwaves is provided in Annex 9.3. SPEI based on Modified Hargreaves

3.2.1 Drought Characteristics

3.2.1.1 Barcelona

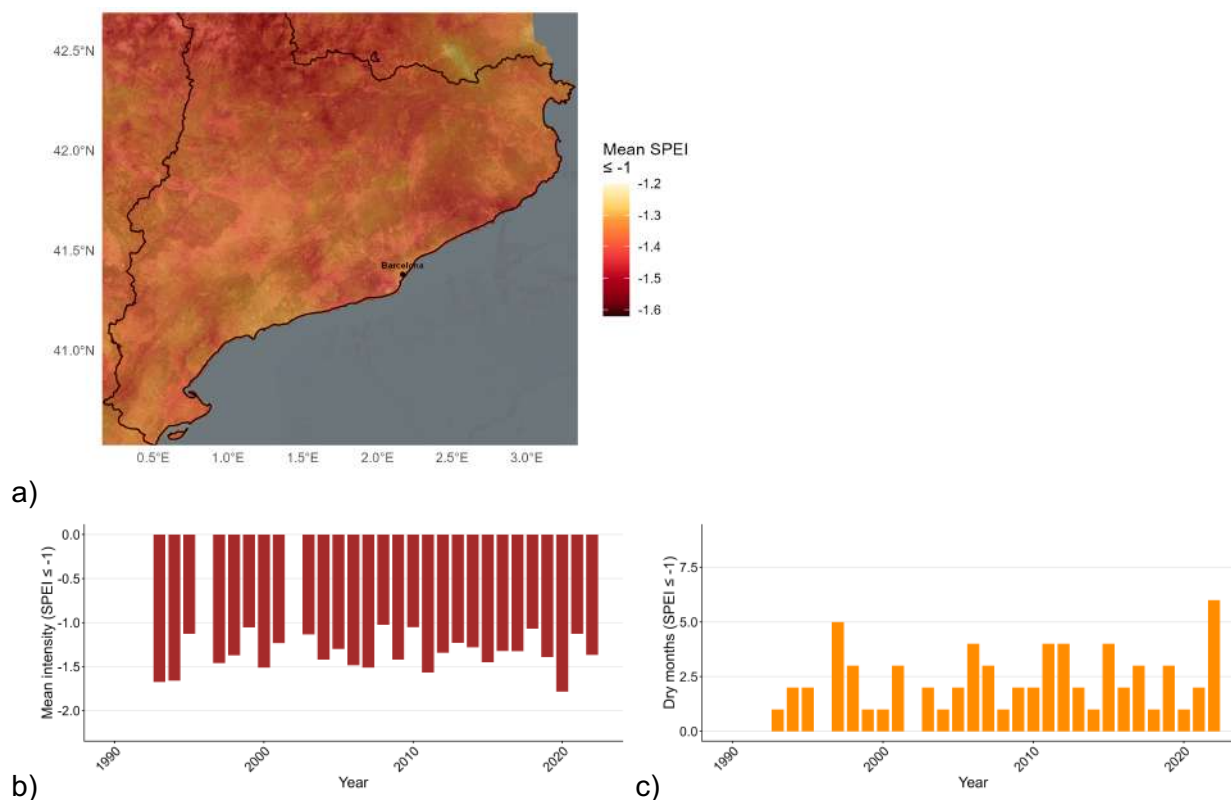
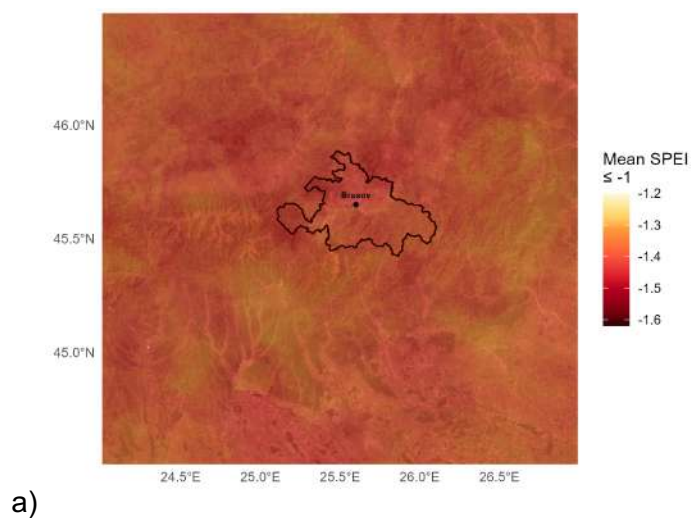


Figure A 8: Drought characteristics for the greater CSA Barcelona area based on the SPEI-1 ≤ -1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.2.1.2 Brasov



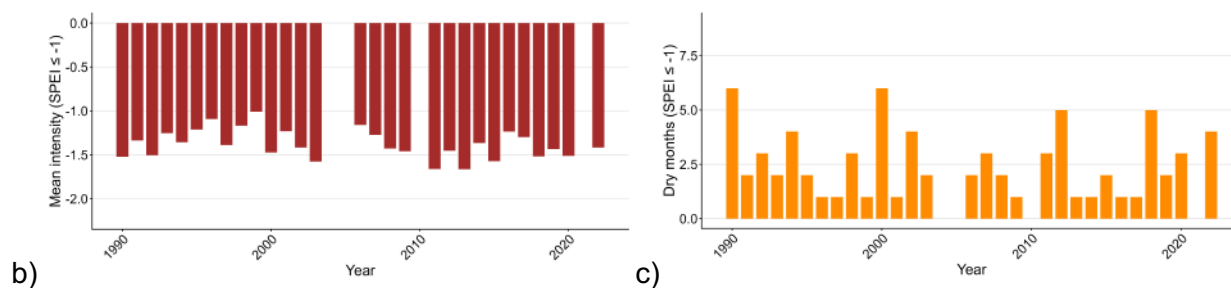


Figure A 9: Drought characteristics for the greater CSA Brasov area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.2.1.3 Prague

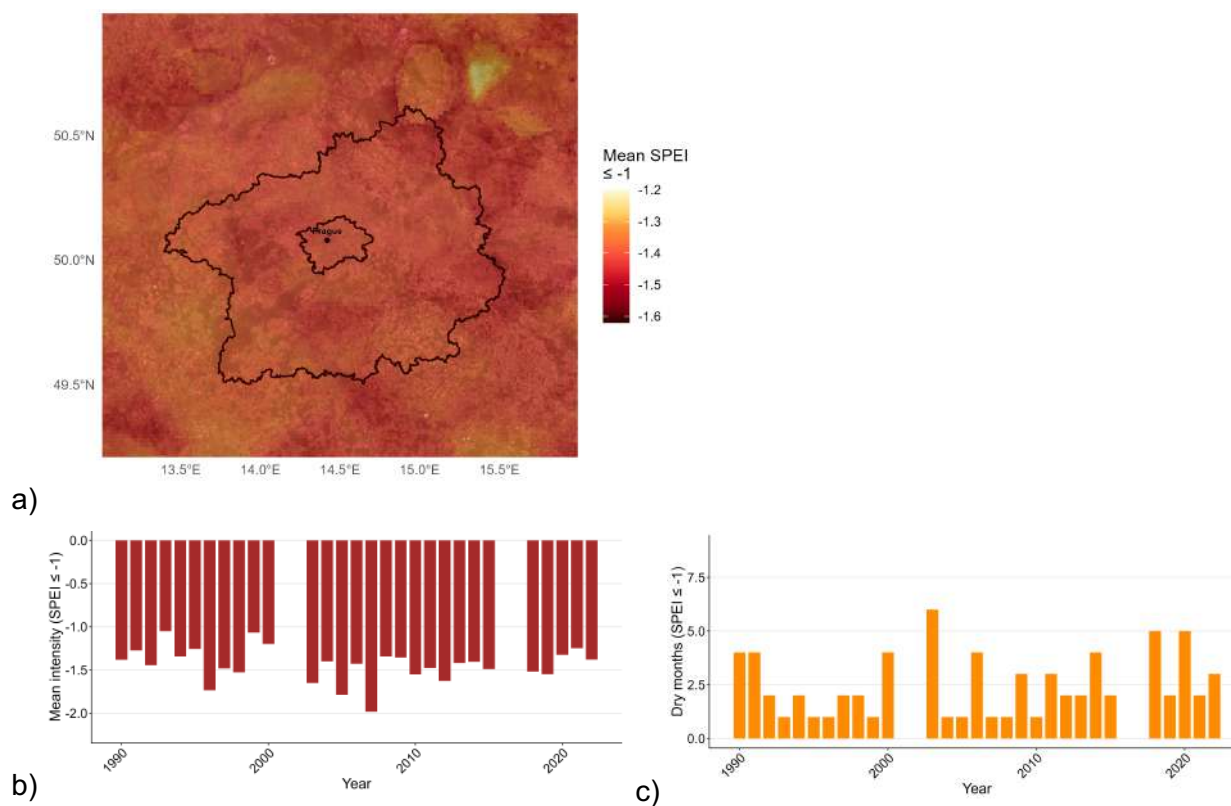


Figure A 10: Drought characteristics for the greater CSA Prague area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.2.2 Wetness Characteristics

3.2.2.1 Leipzig

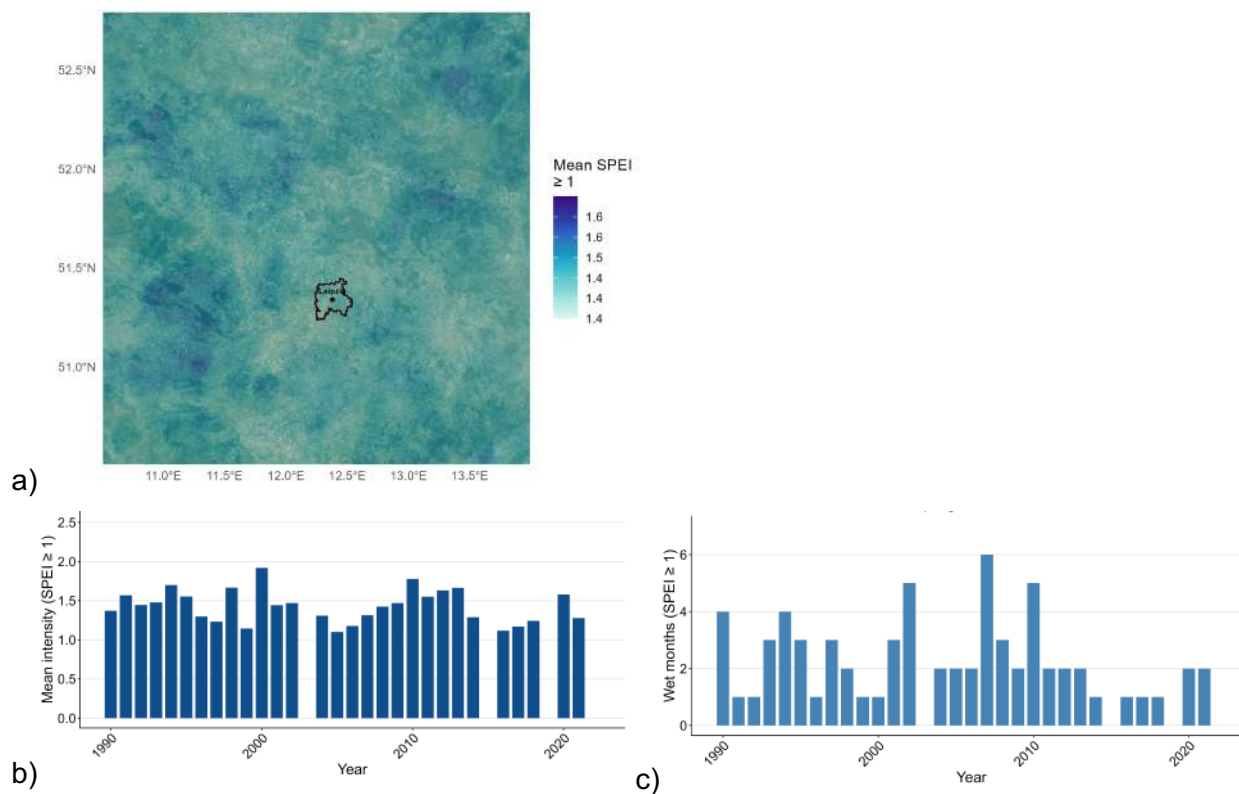
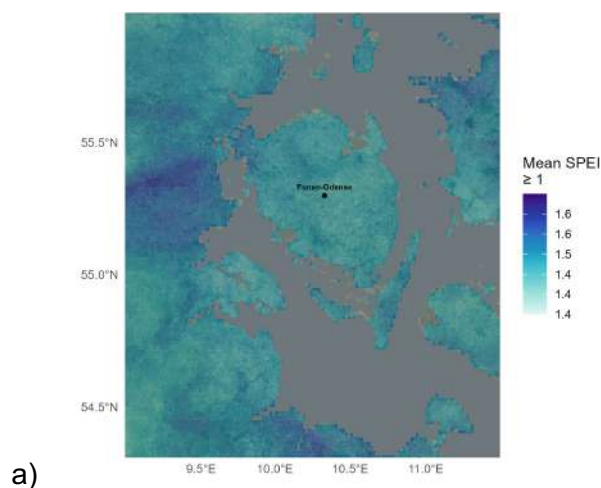


Figure A 11: Wetness characteristics for the greater CSA Leipzig area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.2.2.2 Funen-Odense



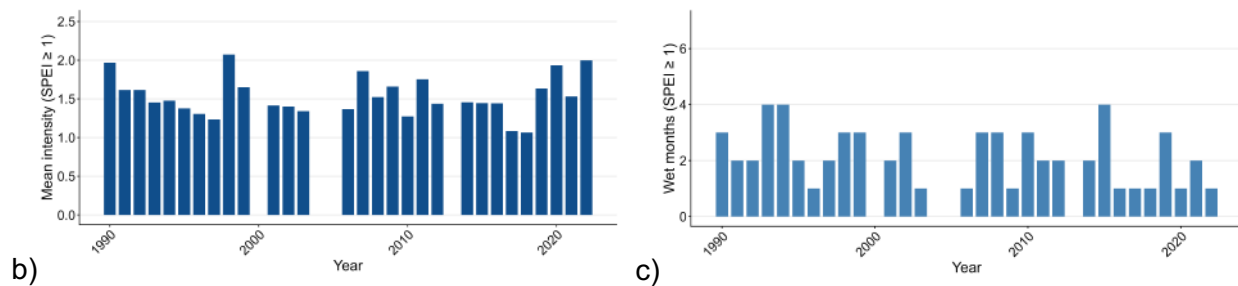


Figure A 12: Wetness characteristics for the greater CSA Funen-Odense area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.2.2.3 Brasov

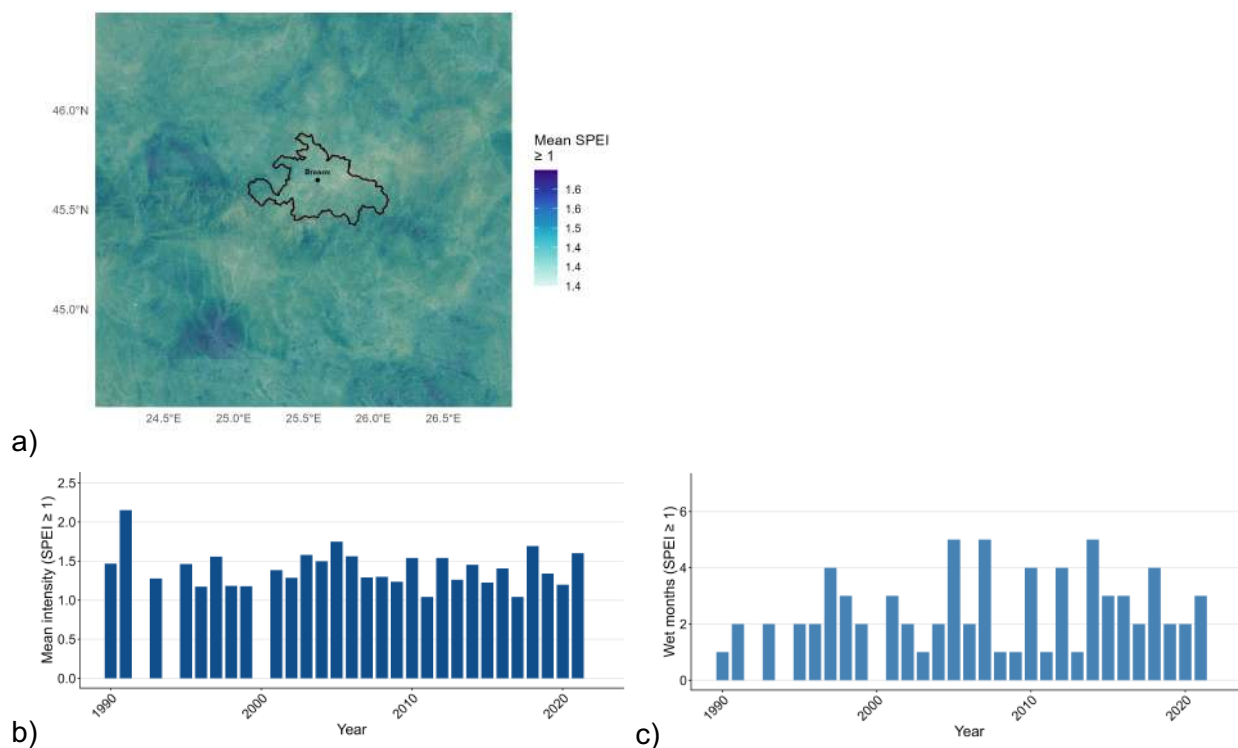


Figure A 13: Wetness characteristics for the greater CSA Brasov area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.2.2.4 Birmingham

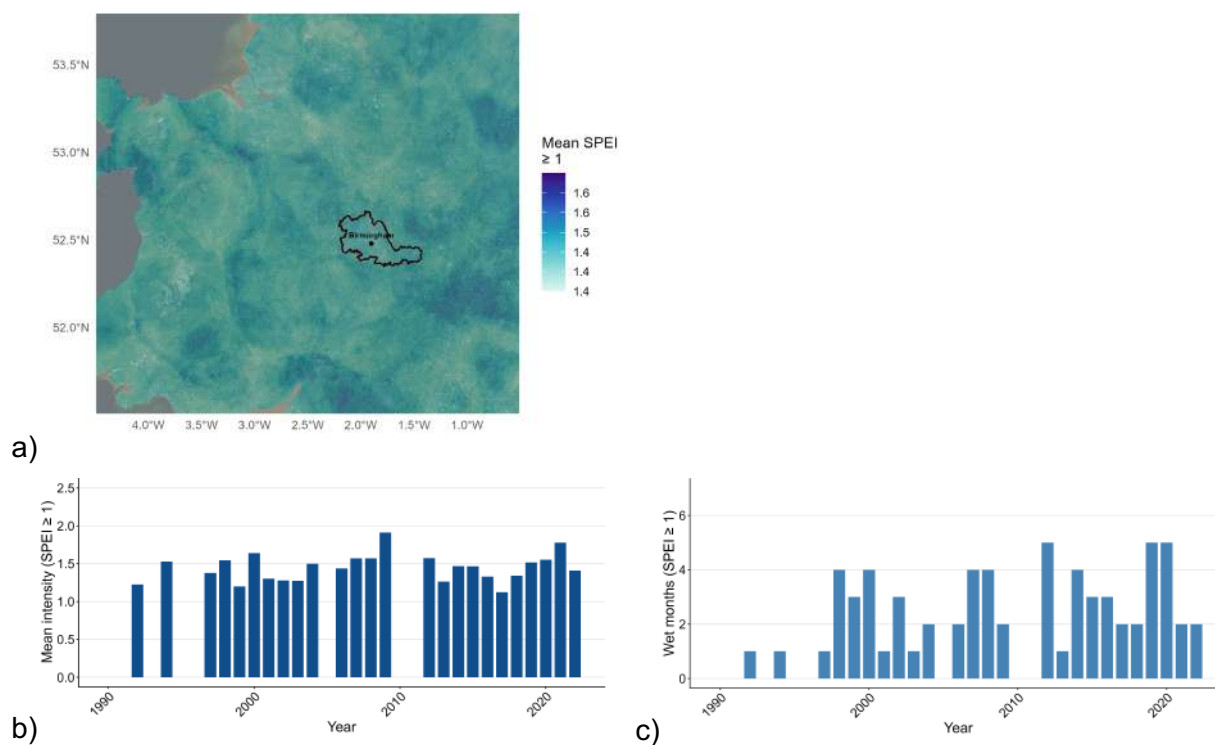
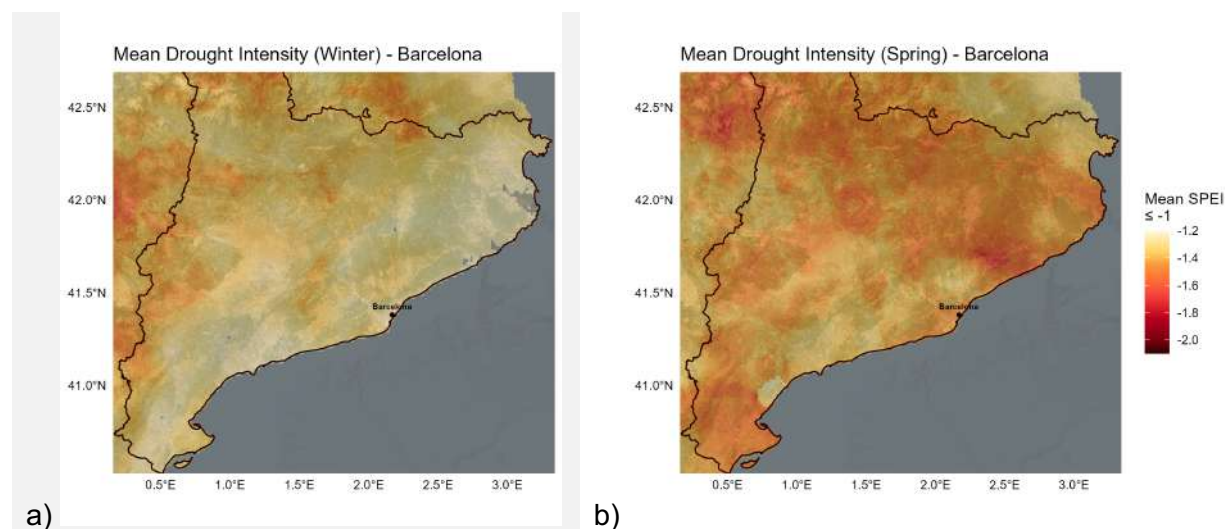


Figure A 14: Wetness characteristics for the greater CSA Birmingham area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.2.3 Seasonal Drought Maps

3.2.3.1 Barcelona



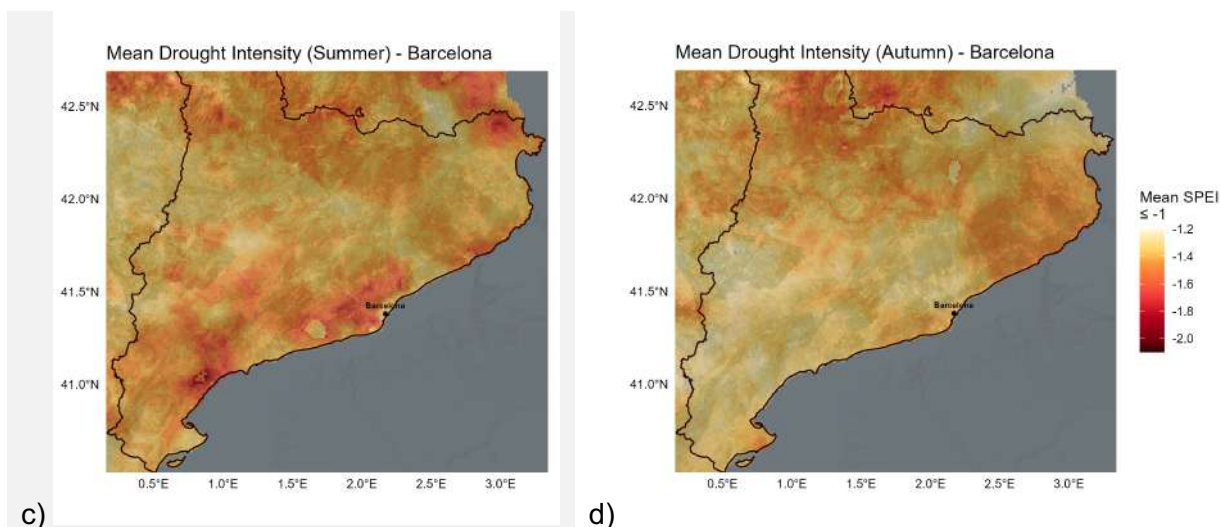
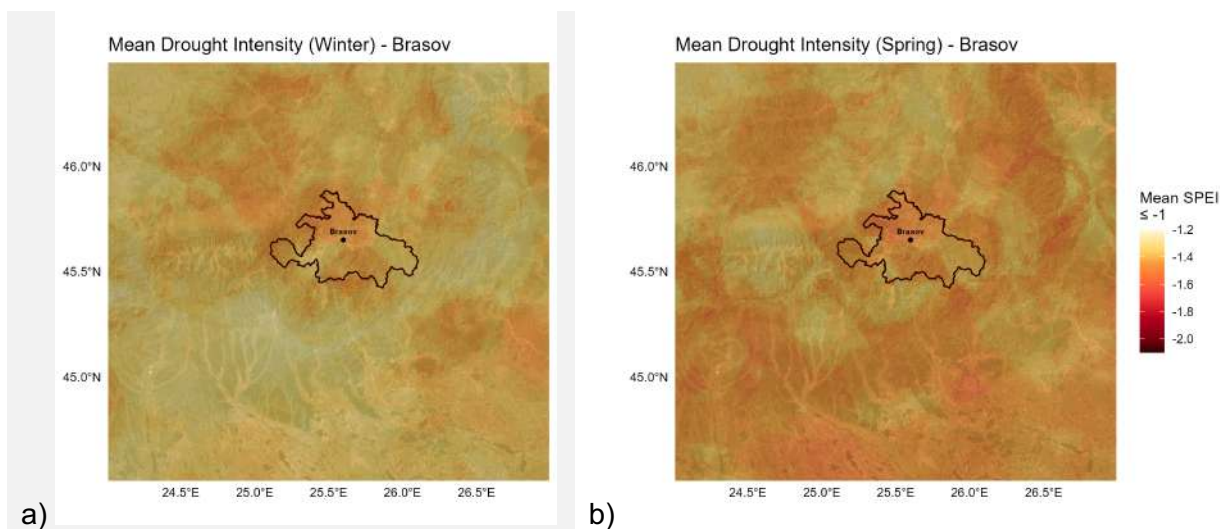


Figure A 15: Spatial distribution of seasonal drought intensity for the greater CSA Barcelona area during 1990-2022 based on the $SPEI-1 \leq 1$ (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.2.3.2 Brasov



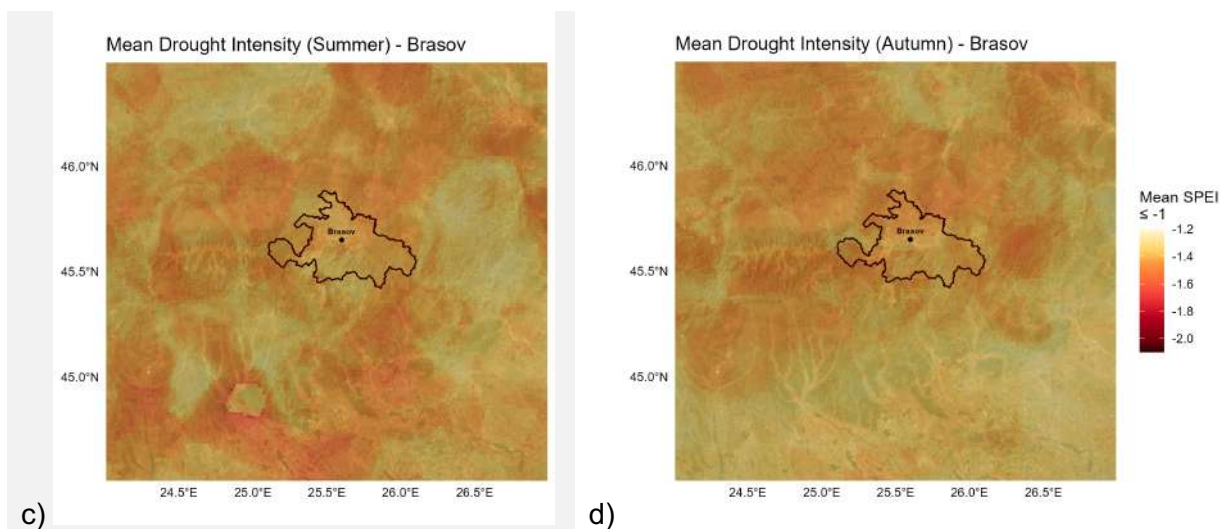
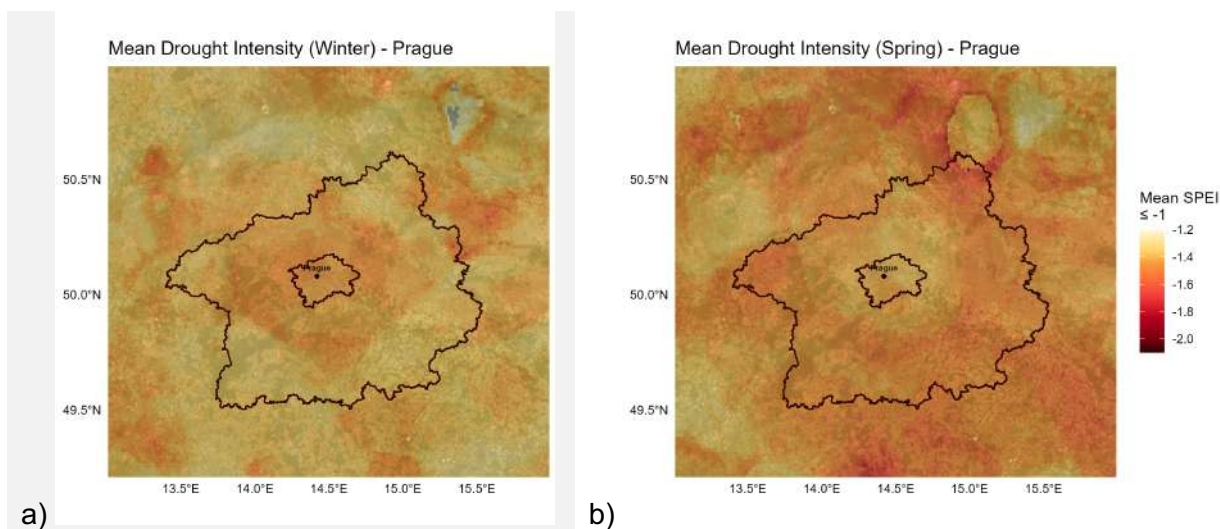


Figure A 16: Spatial distribution of seasonal drought intensity for the greater CSA Barcelona area during 1990-2022 based on the $SPEI-1 \leq 1$ (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.2.3.3 Prague



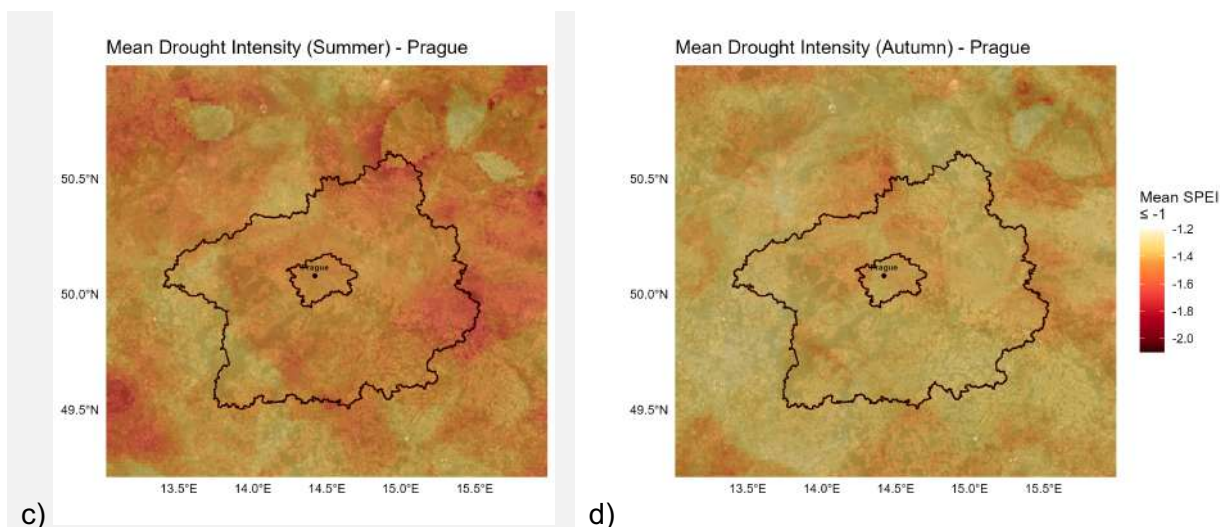
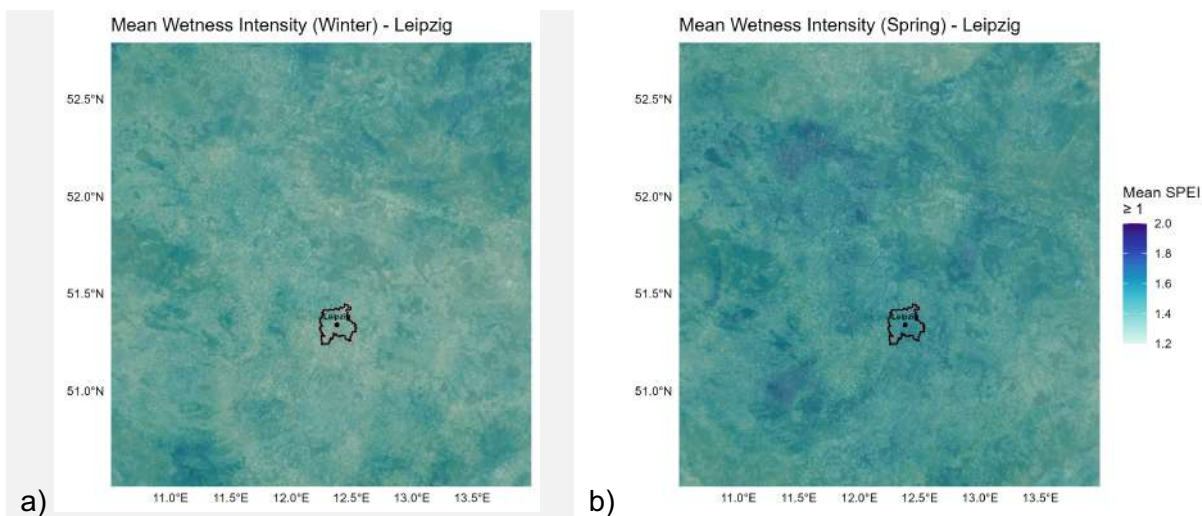


Figure A 17: Spatial distribution of seasonal drought intensity for the greater CSA Prague area during 1990-2022 based on the $SPEI-1 \leq 1$ (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.2.4 Seasonal Wetness Maps

3.2.4.1 Leipzig



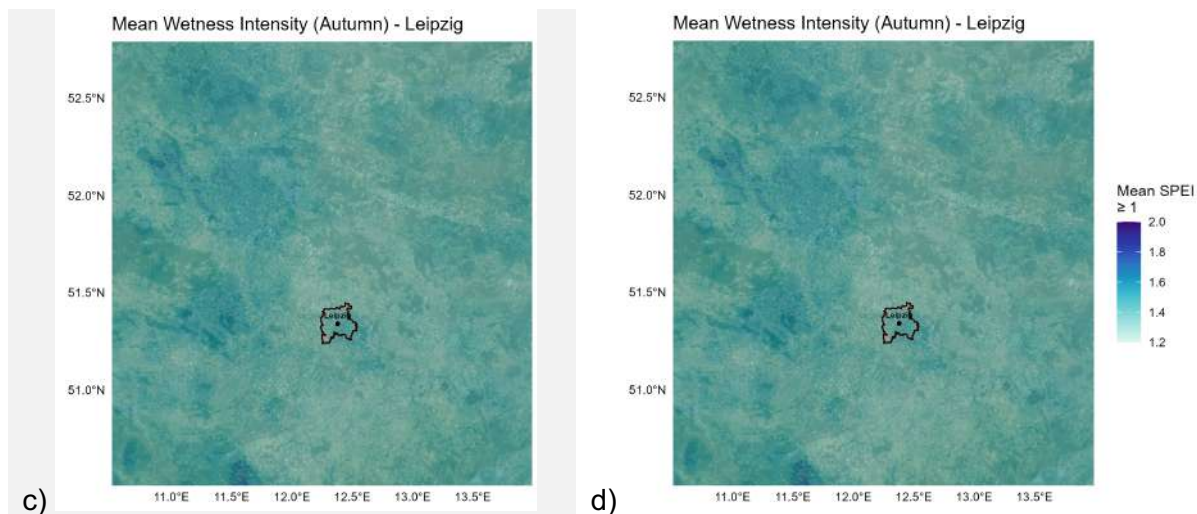
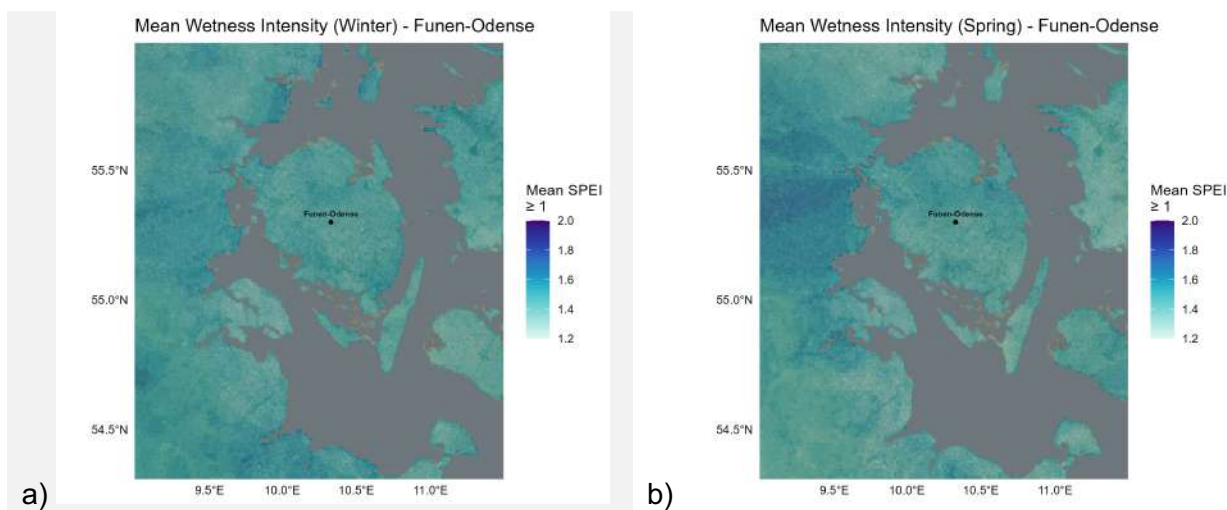


Figure A 18: Spatial distribution of seasonal wetness intensity for the greater CSA Birmingham area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.2.4.2 Funen-Odense



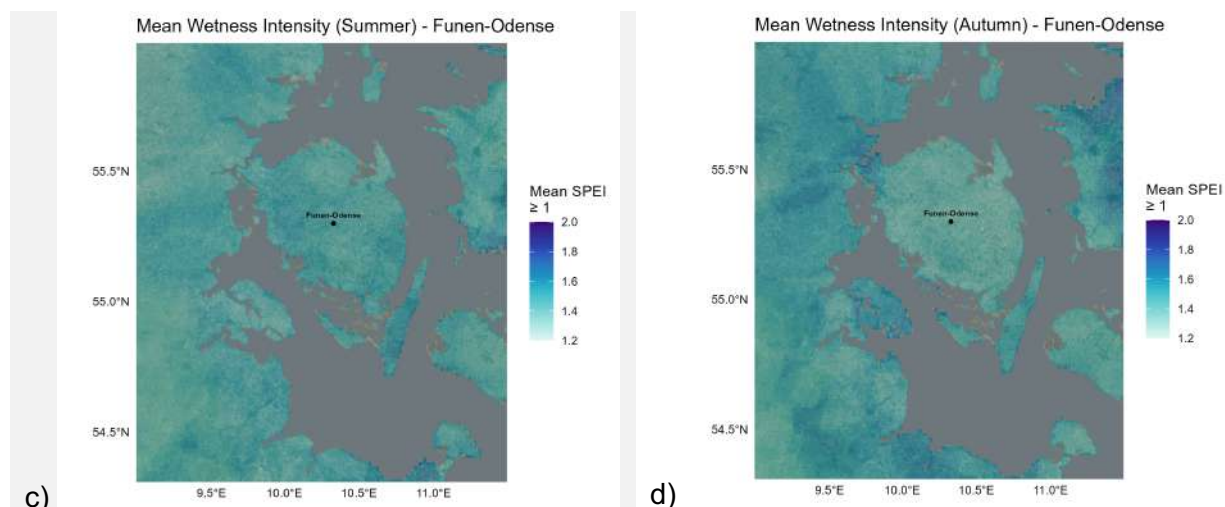
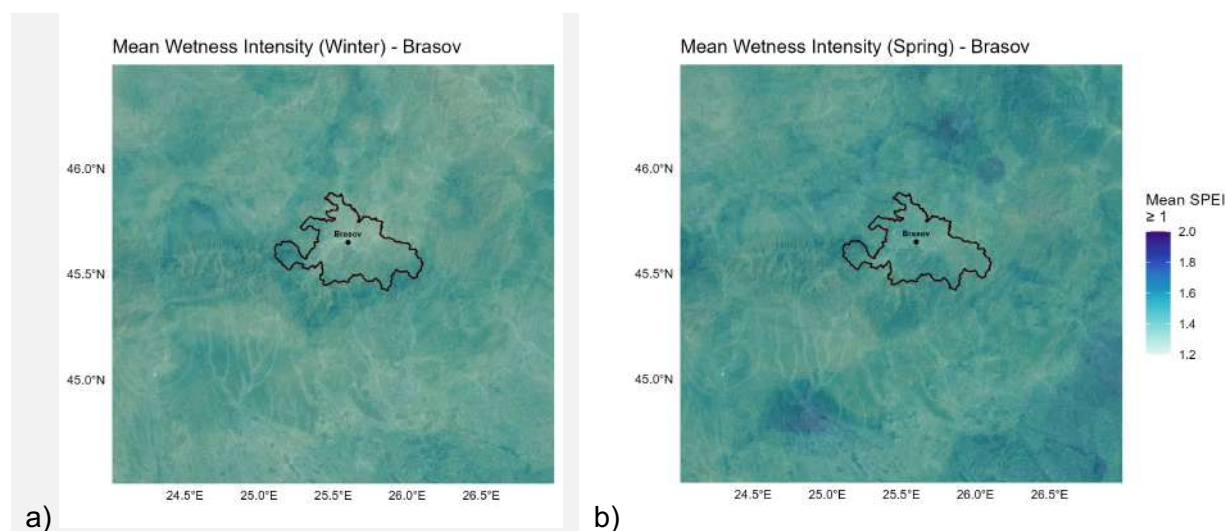


Figure A 19: Spatial distribution of seasonal wetness intensity for the greater CSA Funen-Odense area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.2.4.3 Brasov



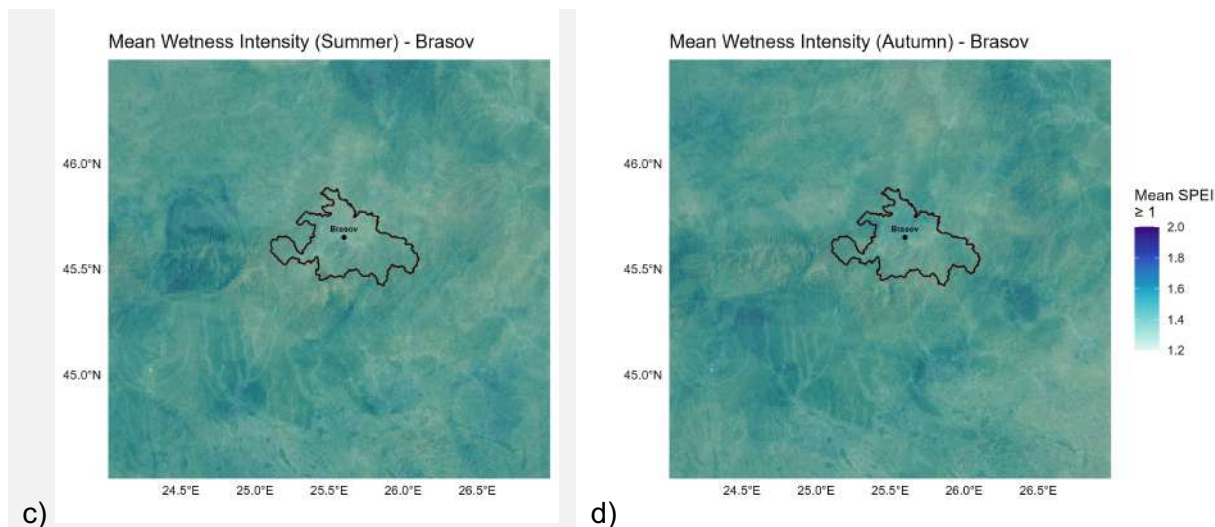
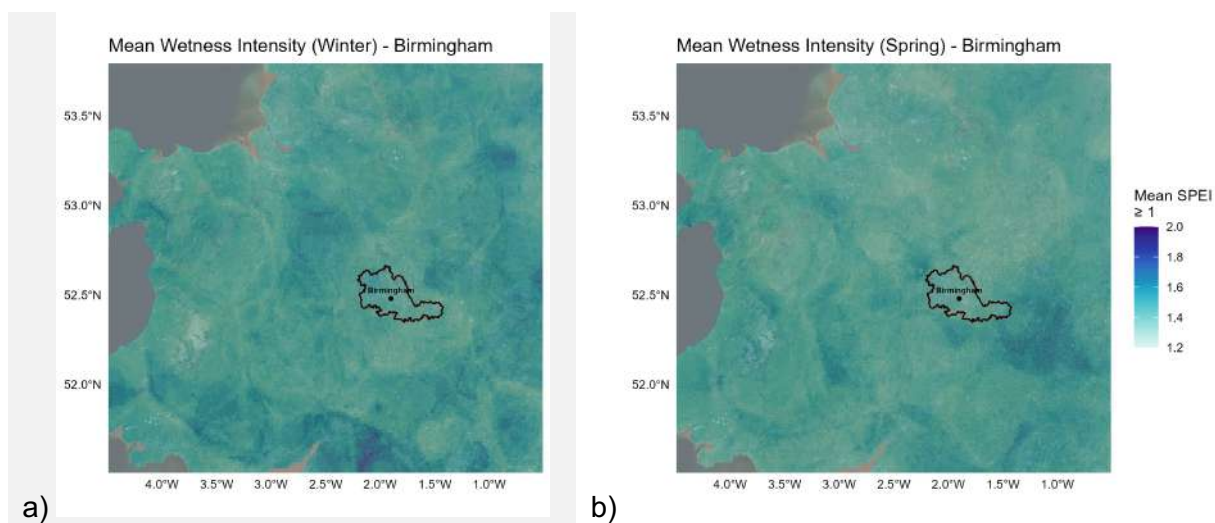


Figure A 20: Spatial distribution of seasonal wetness intensity for the greater CSA Brasov area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.2.4.4 Birmingham



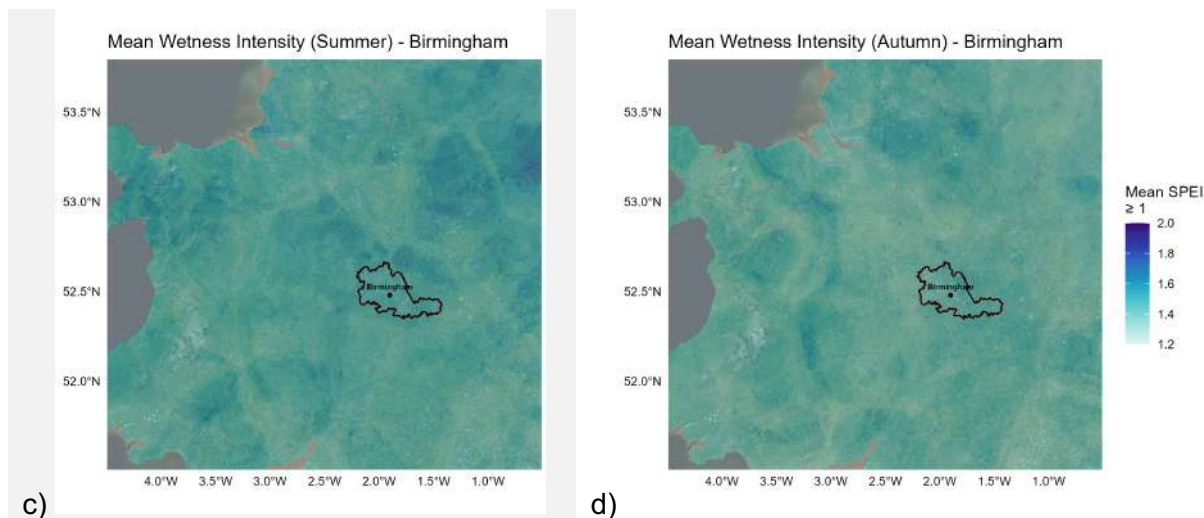


Figure A 21: Spatial distribution of seasonal wetness intensity for the greater CSA Birmingham area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.3 SPEI based on Modified Hargreaves and E-OBS Data

3.3.1 Drought Characteristics

3.3.1.1 Barcelona

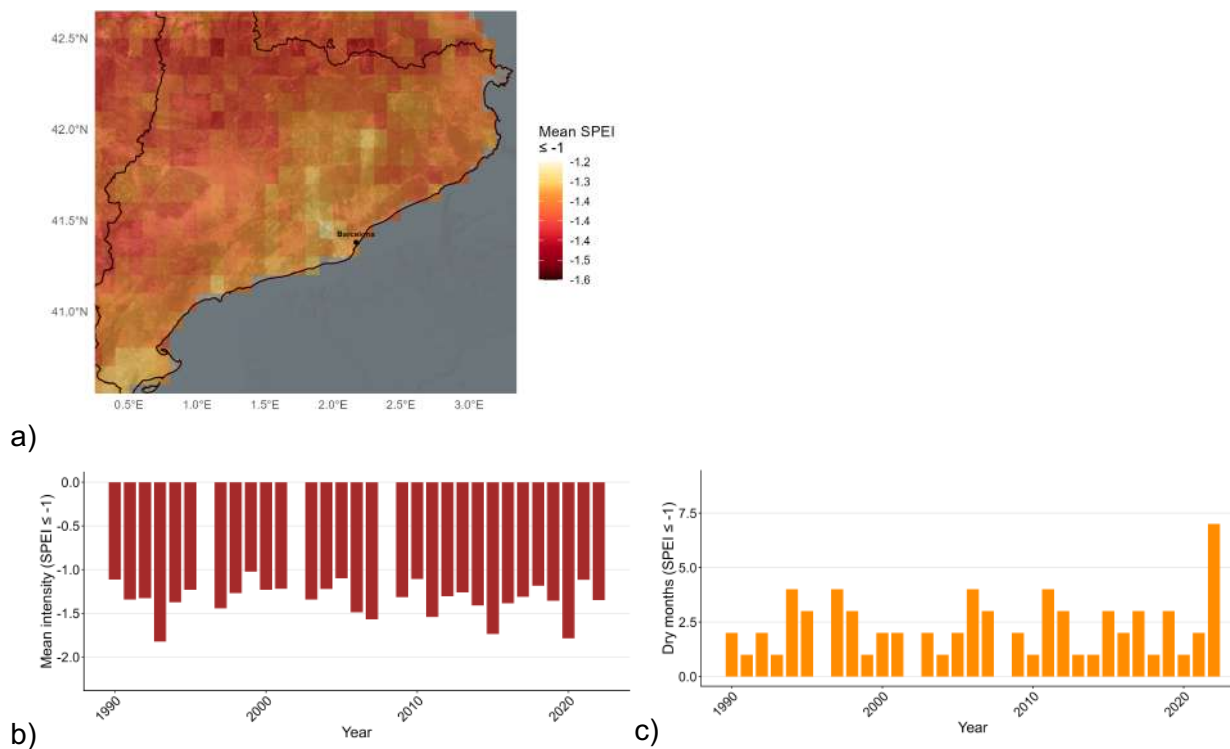


Figure A 22: Drought characteristics for the greater CSA Barcelona area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.3.1.2 Brasov

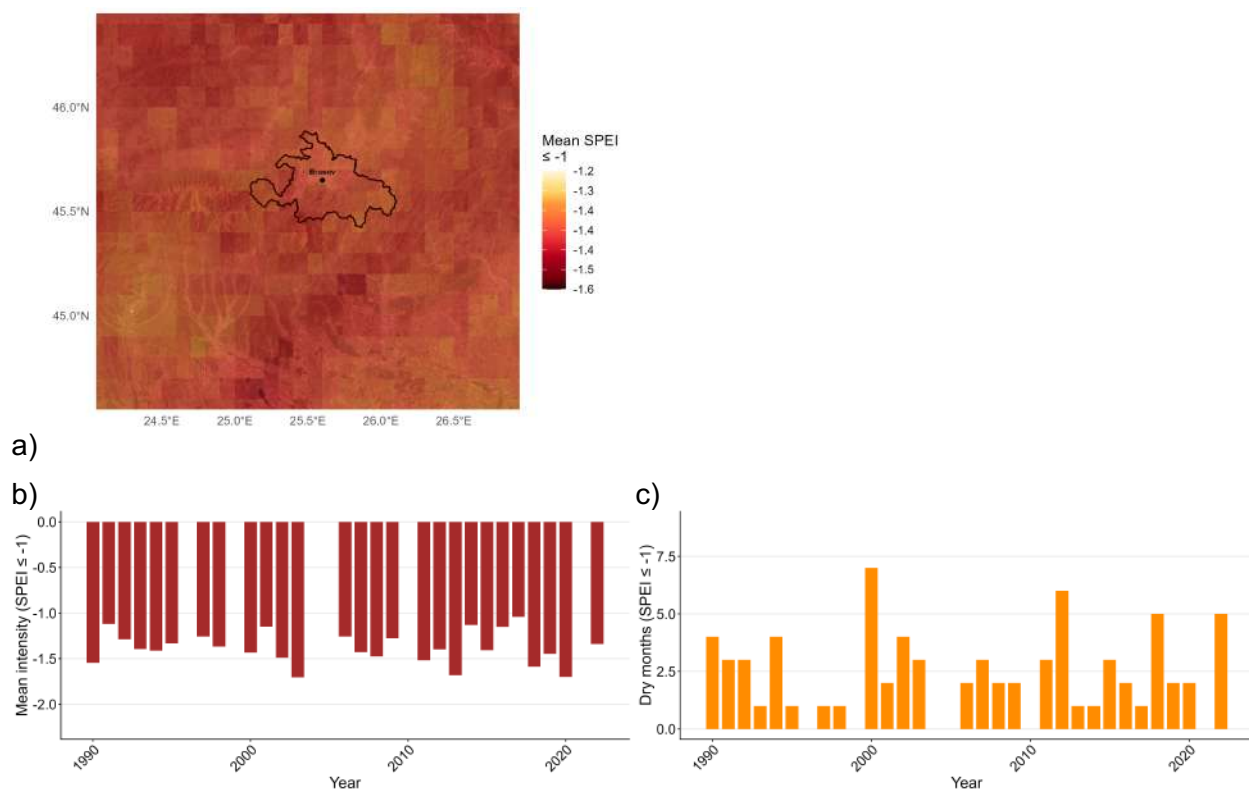
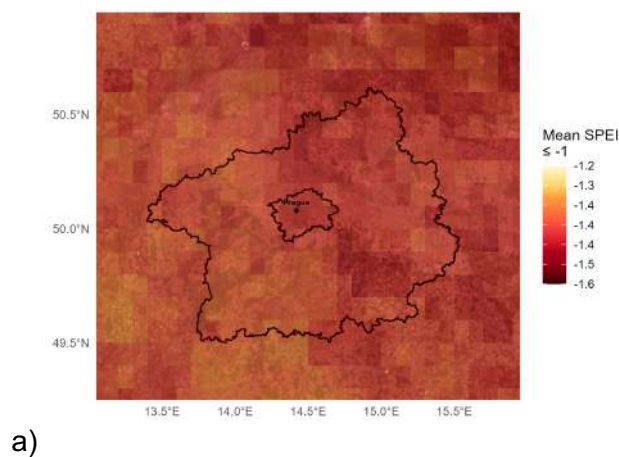


Figure A 23: Drought characteristics for the greater CSA Brasov area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.3.1.3 Prague



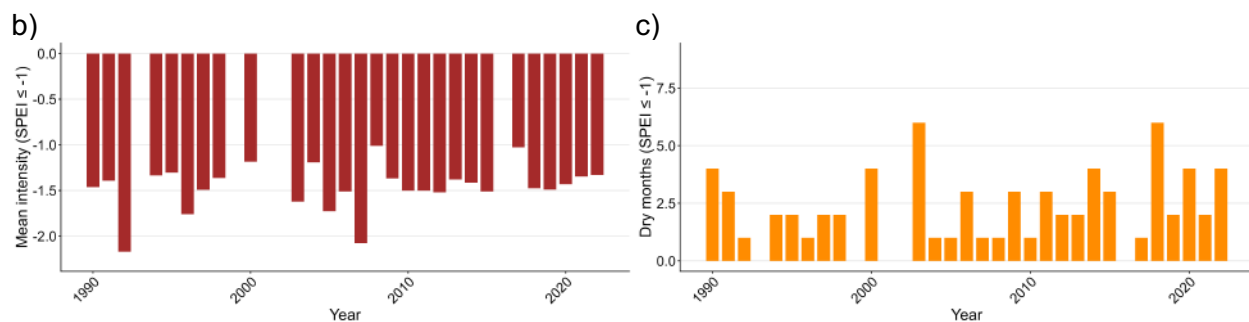


Figure A 24: Drought characteristics for the greater CSA Prague area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.3.2 Wetness Characteristics

3.3.2.1 Leipzig

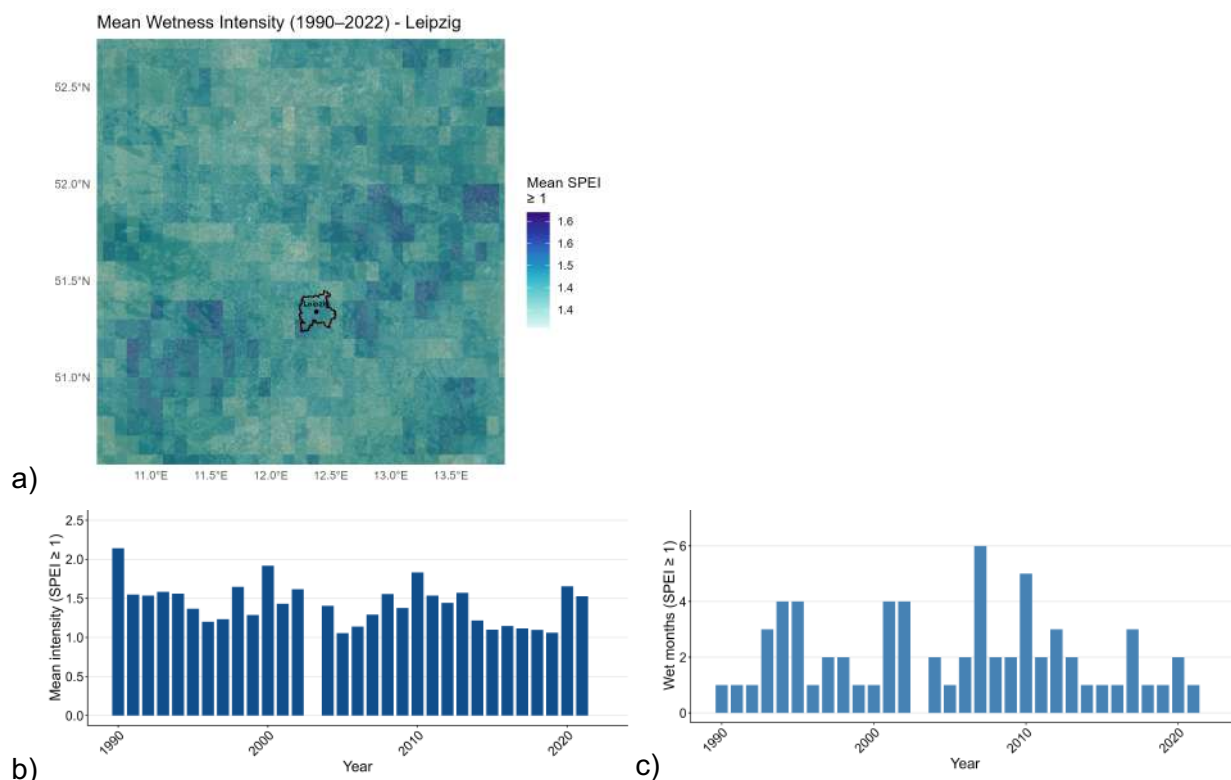


Figure A 25: Wetness characteristics for the greater CSA Leipzig area based on the $SPEI-1 \geq 1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.3.2.2 Funen-Odense

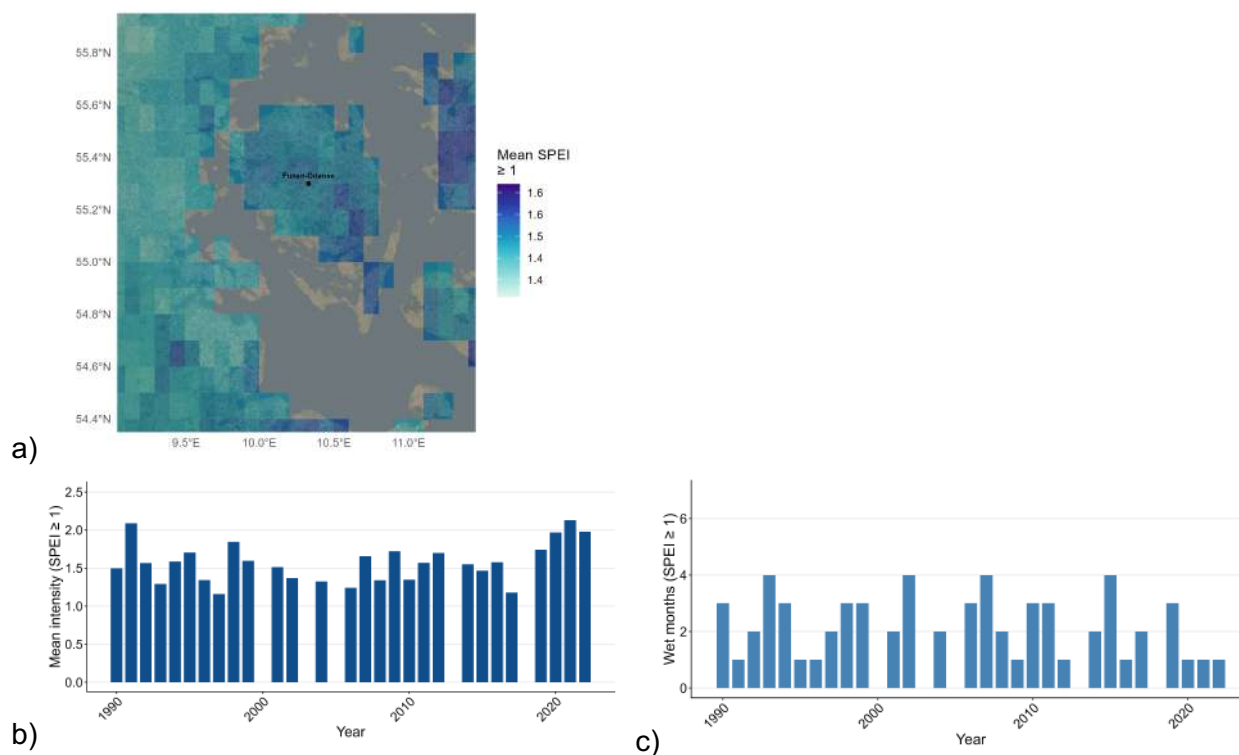
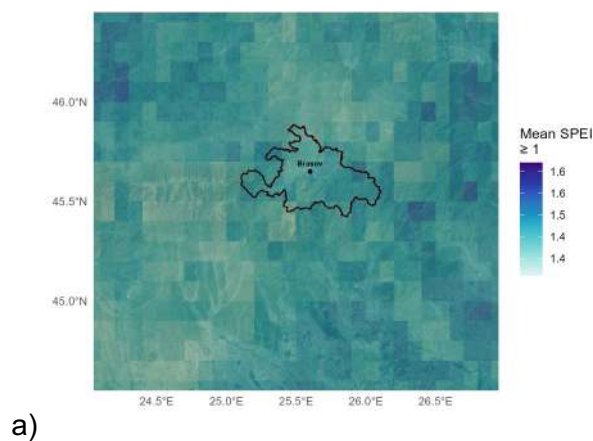


Figure A 26: Wetness characteristics for the greater CSA Funen-Odense area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.3.2.3 Brasov



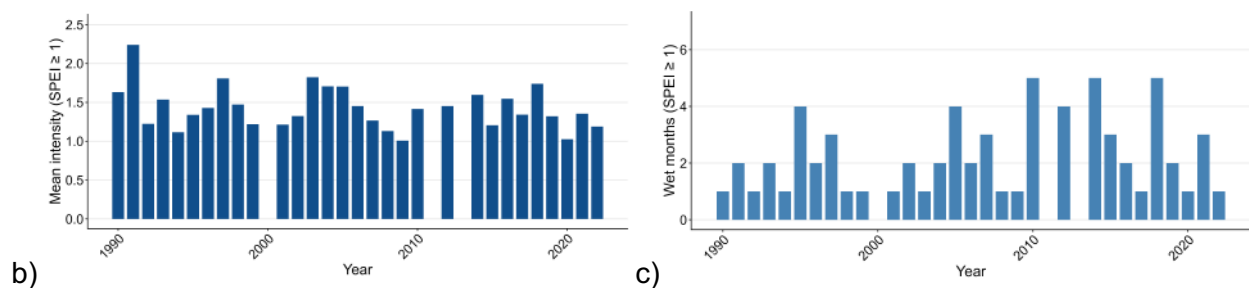


Figure A 27: Wetness characteristics for the greater CSA Brasov area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.3.2.4 Birmingham

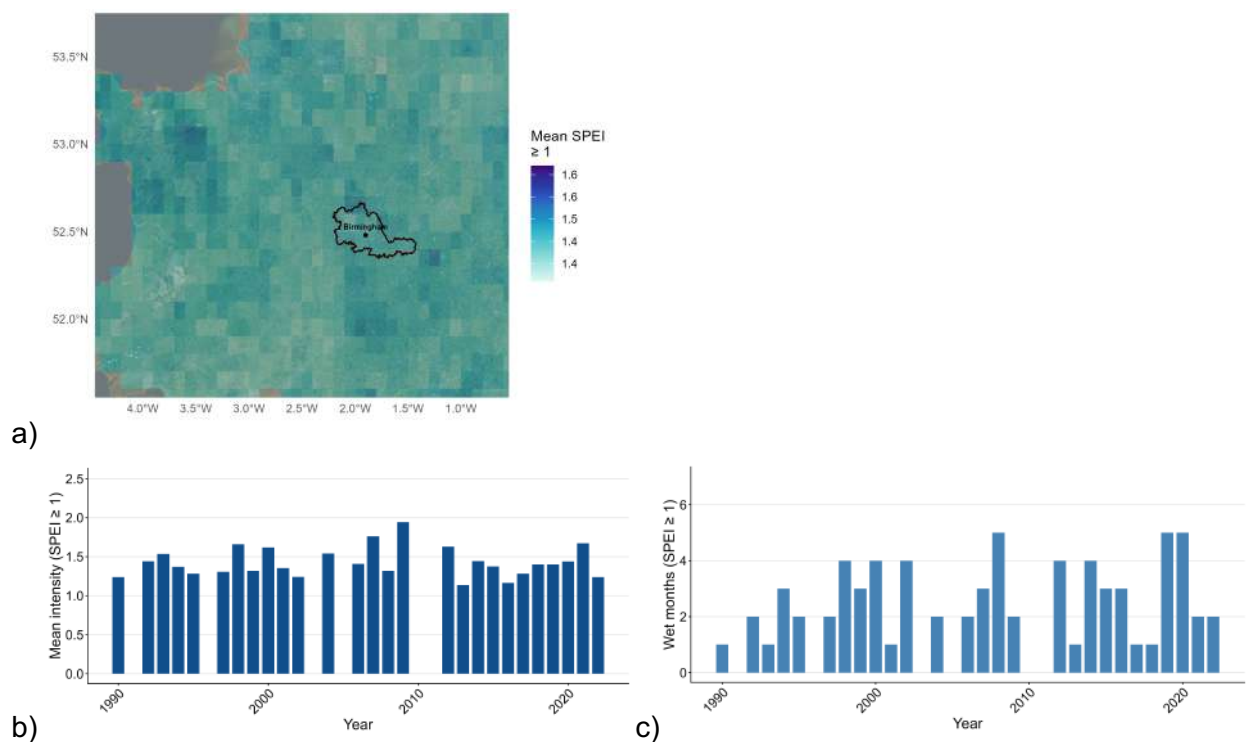


Figure A 28: Wetness characteristics for the greater CSA Birmingham area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.3.3 Seasonal Drought Maps

3.3.3.1 Barcelona

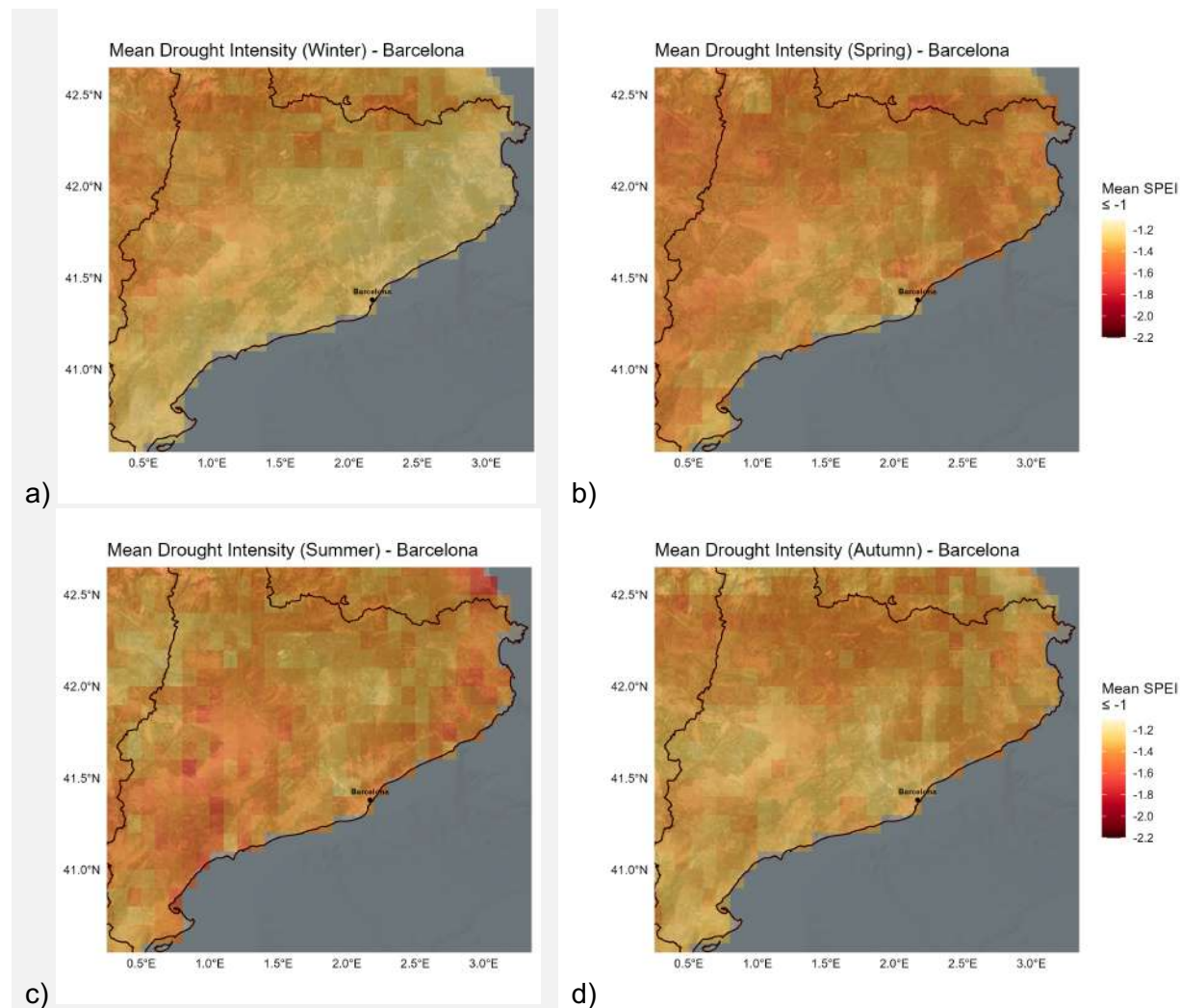


Figure A 29: Spatial distribution of seasonal drought intensity for the greater CSA Barcelona area during 1990-2022 based on the SPEI-1 ≤ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.3.3.2 Brasov

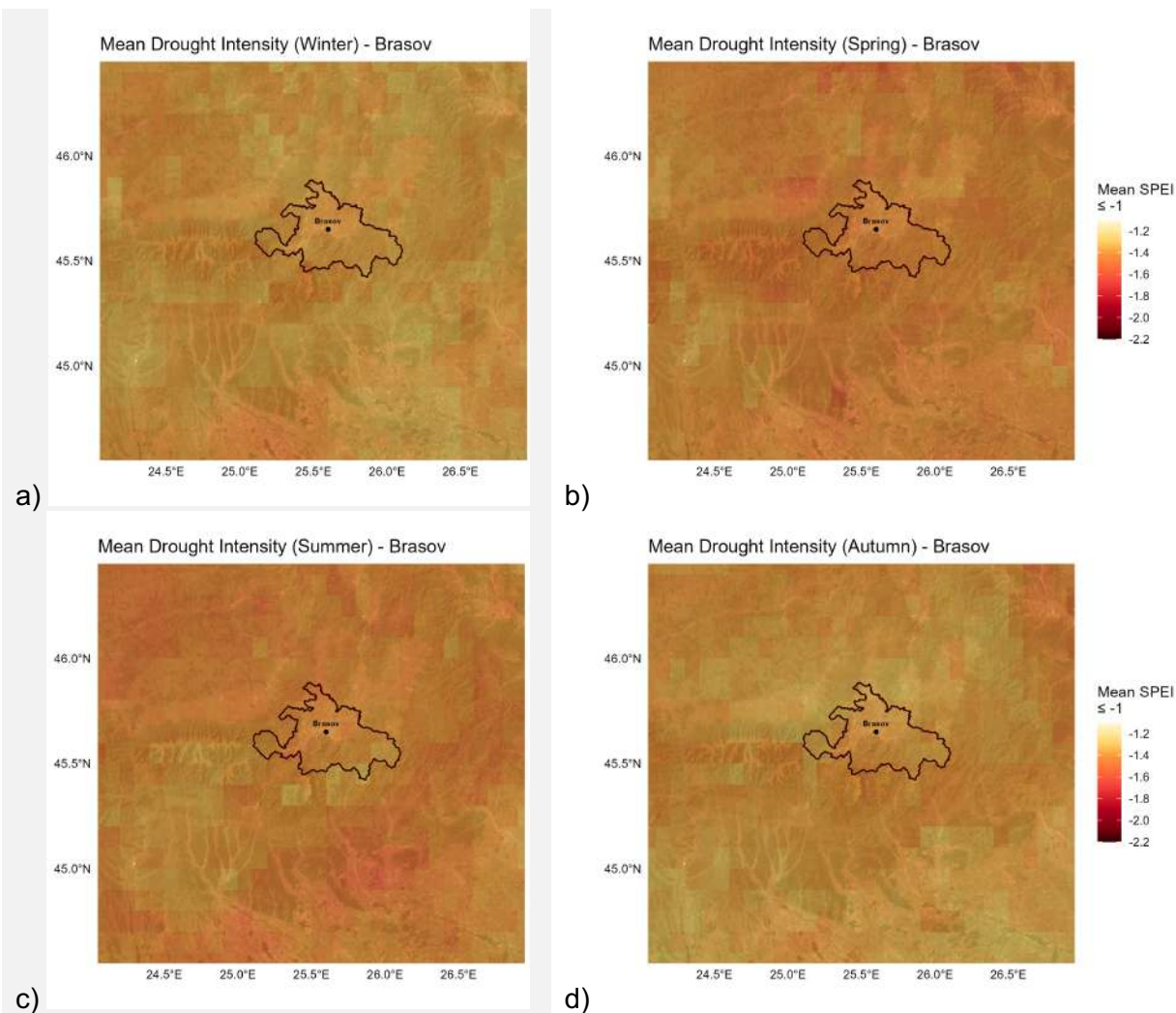


Figure A 30: Spatial distribution of seasonal drought intensity for the greater CSA Brasov area during 1990-2022 based on the SPEI-1 ≤ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.3.3.3 Prague

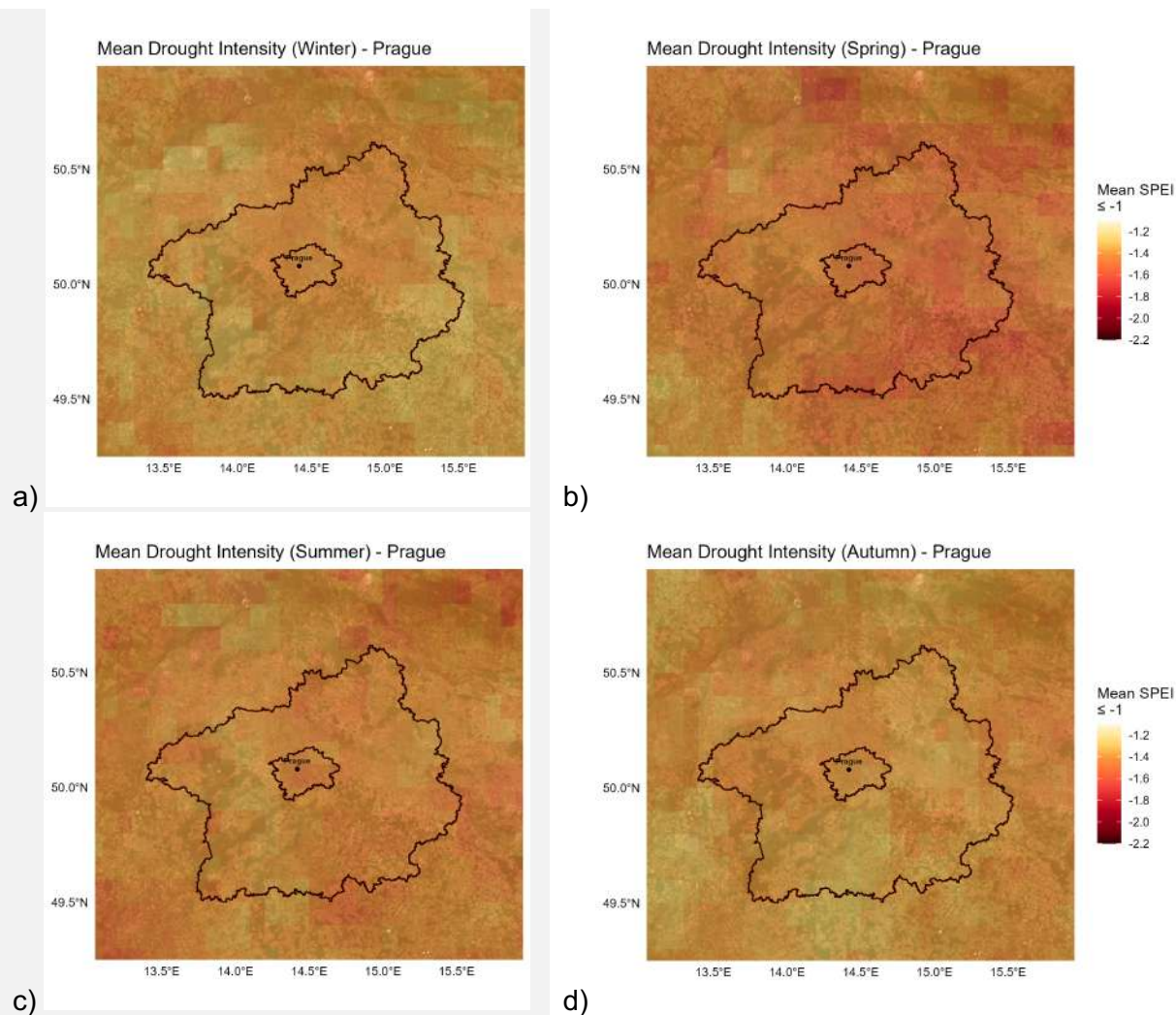


Figure A 31: Spatial distribution of seasonal drought intensity for the greater CSA Prague area during 1990-2022 based on the $SPEI-1 \leq 1$ (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.3.4 Seasonal Wetness Maps

3.3.4.1 Leipzig

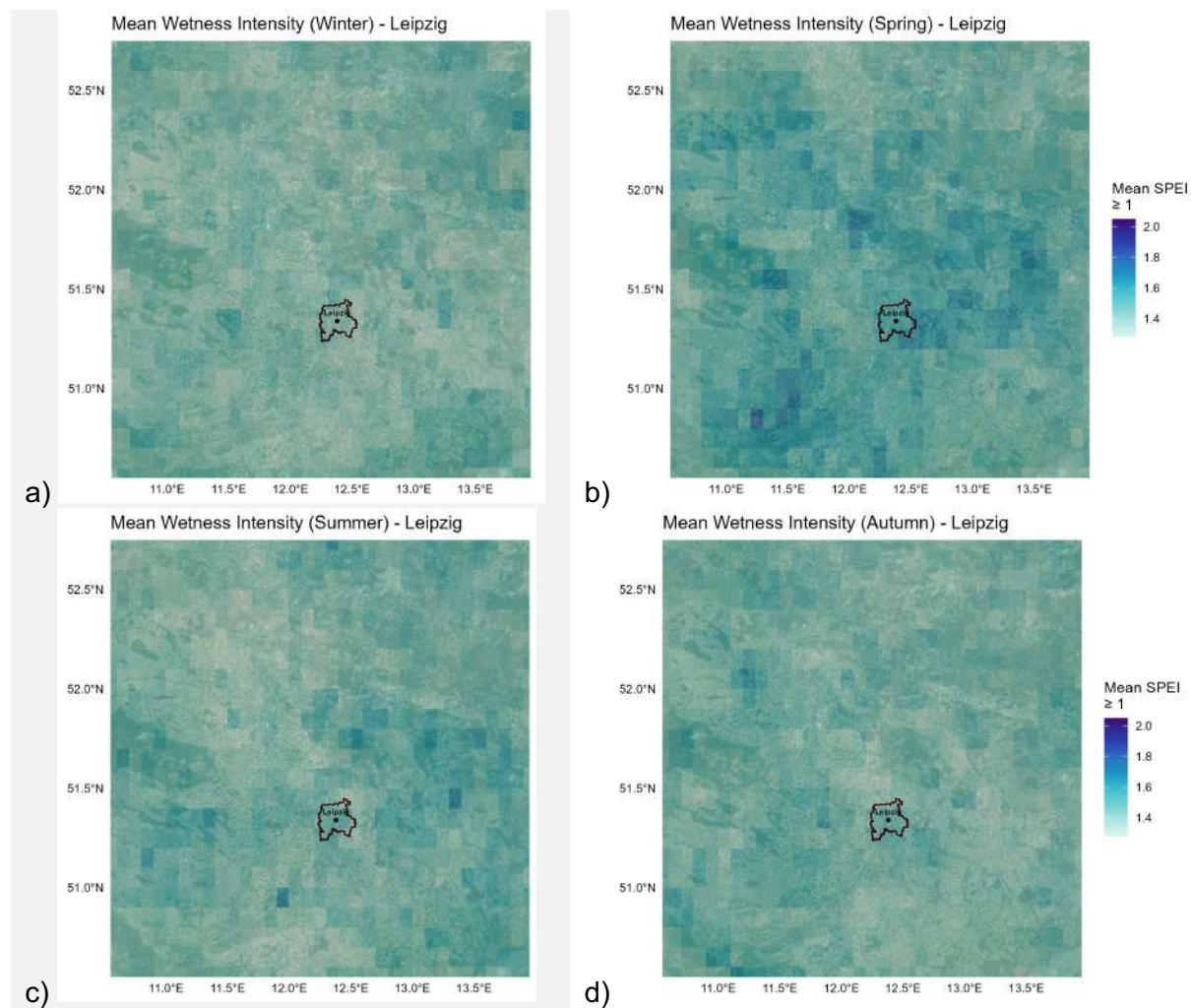


Figure A 32: Spatial distribution of seasonal wetness intensity for the greater CSA Leipzig area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.3.4.2 Funen-Odense

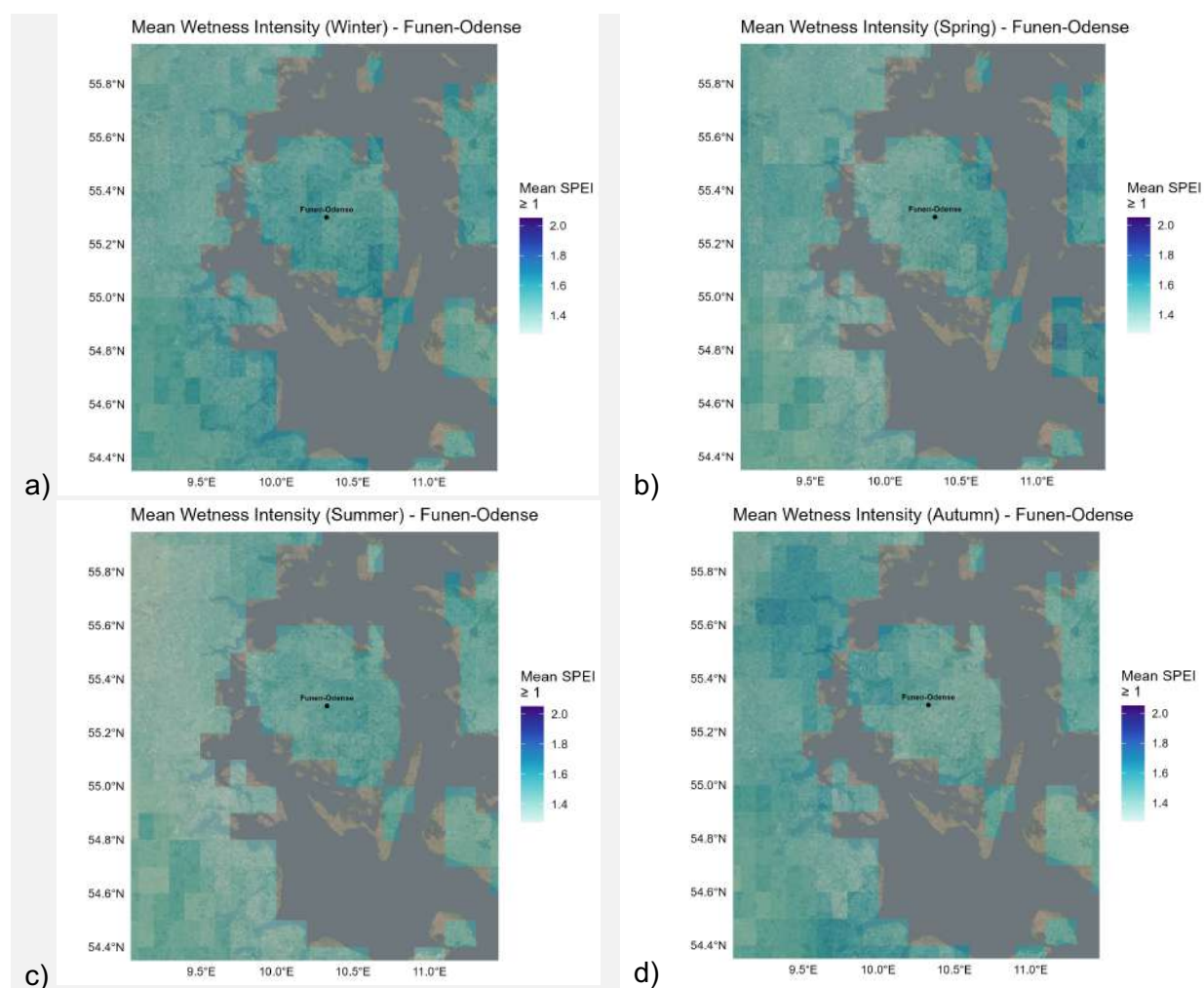


Figure A 33: Spatial distribution of seasonal wetness intensity for the greater CSA Funen-Odense area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.3.4.3 Brasov

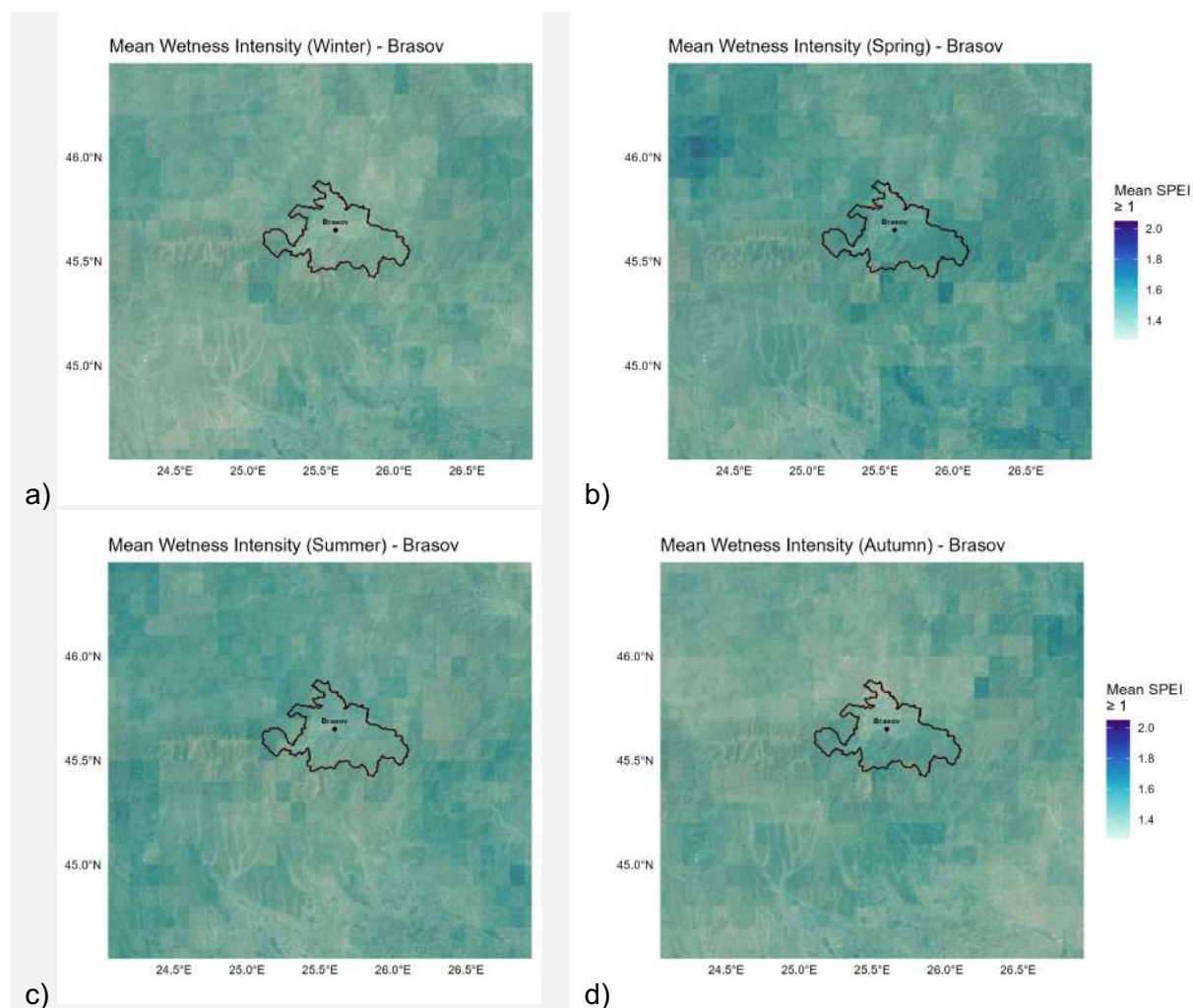


Figure A 34: Spatial distribution of seasonal wetness intensity for the greater CSA Brasov area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.3.4.4 Birmingham

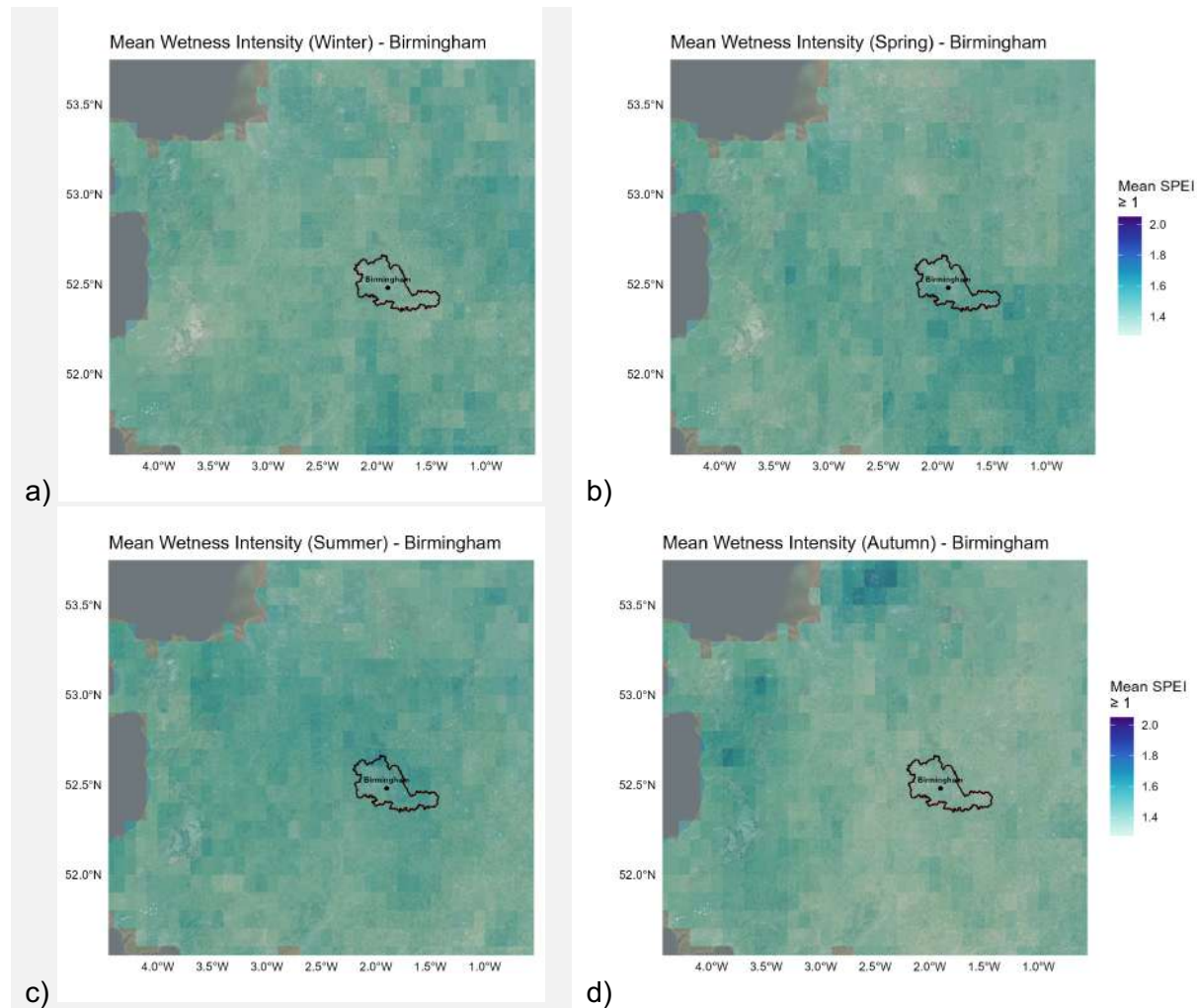


Figure A 35: Spatial distribution of seasonal wetness intensity for the greater CSA Birmingham area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

3.4 Comparative analysis of SPEI

This section presents a comparative temporal analysis of the SPEI results presented in the previous sections, derived from different datasets and PET formulations for the selected CSAs, highlighting similarities and differences in temporal variability and drought/wetness dynamics.

3.4.1 Athens

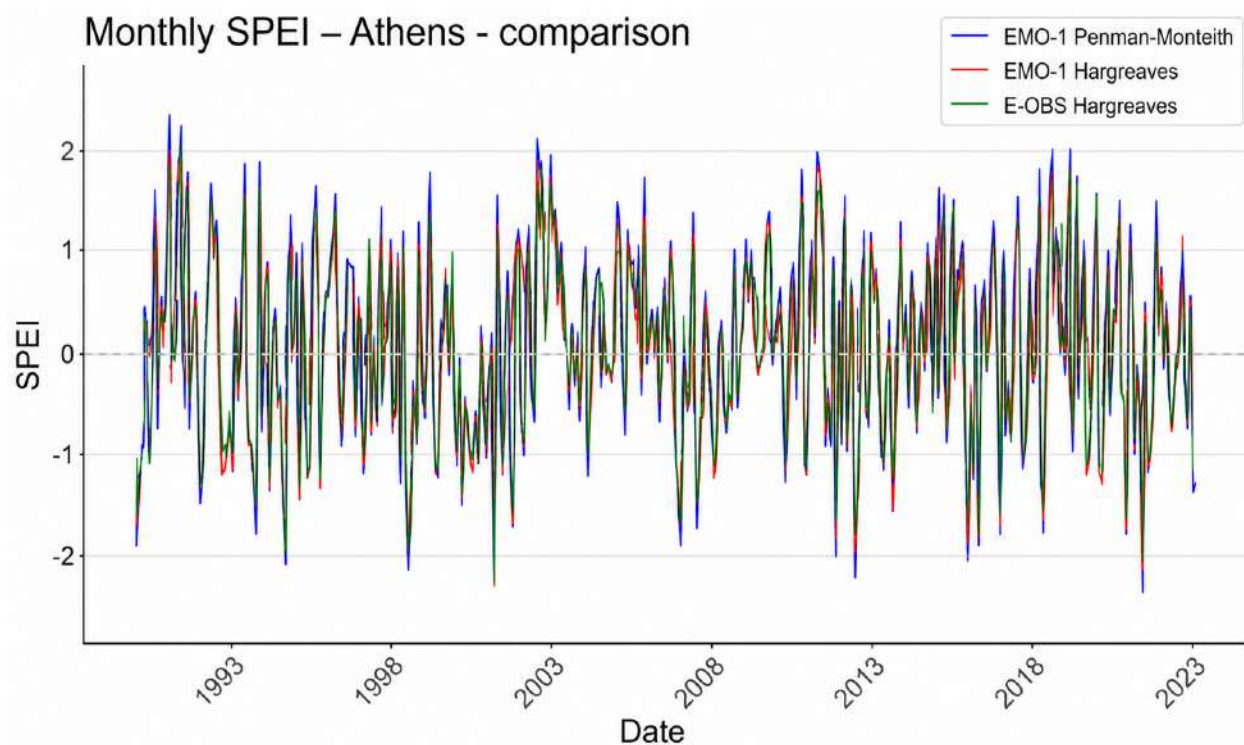


Figure A 36: Temporal comparison of monthly SPEI distributions for the greater CSA Athens area based on the EMO-1 Penman–Monteith, EMO-1 Modified Hargreaves, and E-OBS Modified Hargreaves approaches during the reference period 1990–2022.

3.4.2 Barcelona

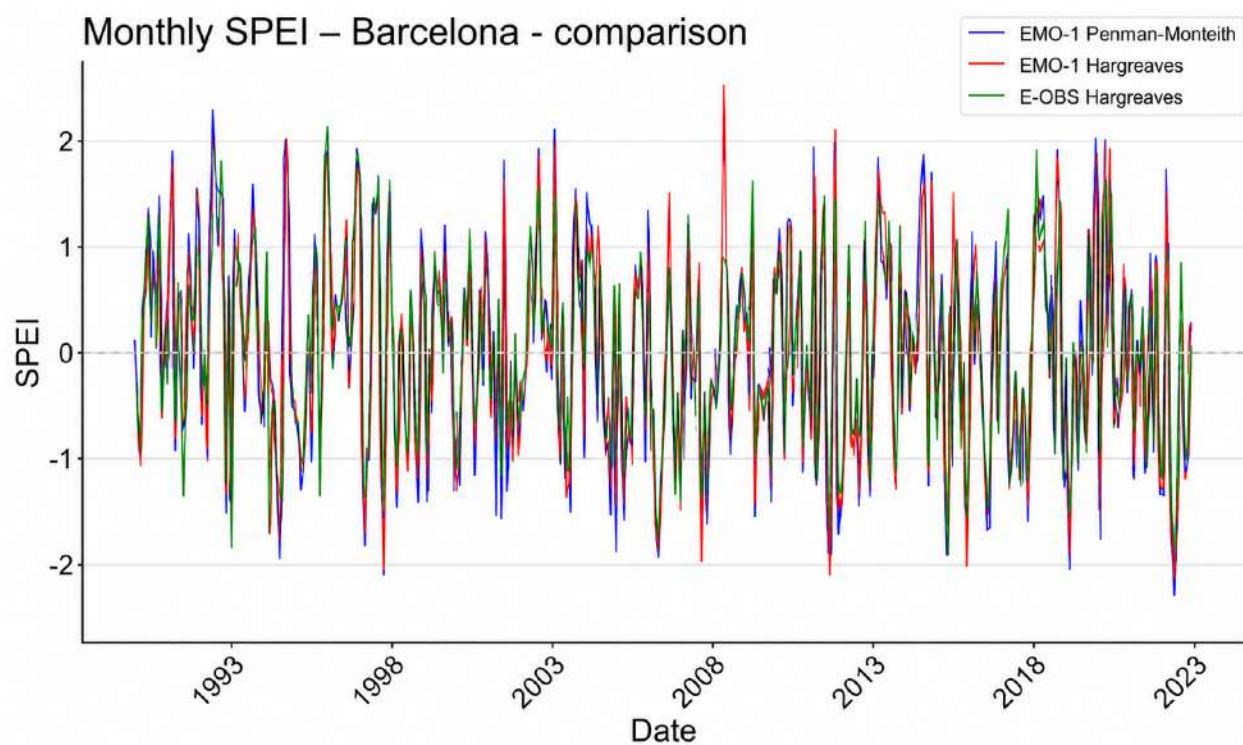


Figure A 37: Temporal comparison of monthly SPEI distributions for the greater CSA Barcelona area based on the EMO-1 Penman–Monteith, EMO-1 Modified Hargreaves, and E-OBS Modified Hargreaves approaches during the reference period 1990–2022.

3.4.3 Birmingham

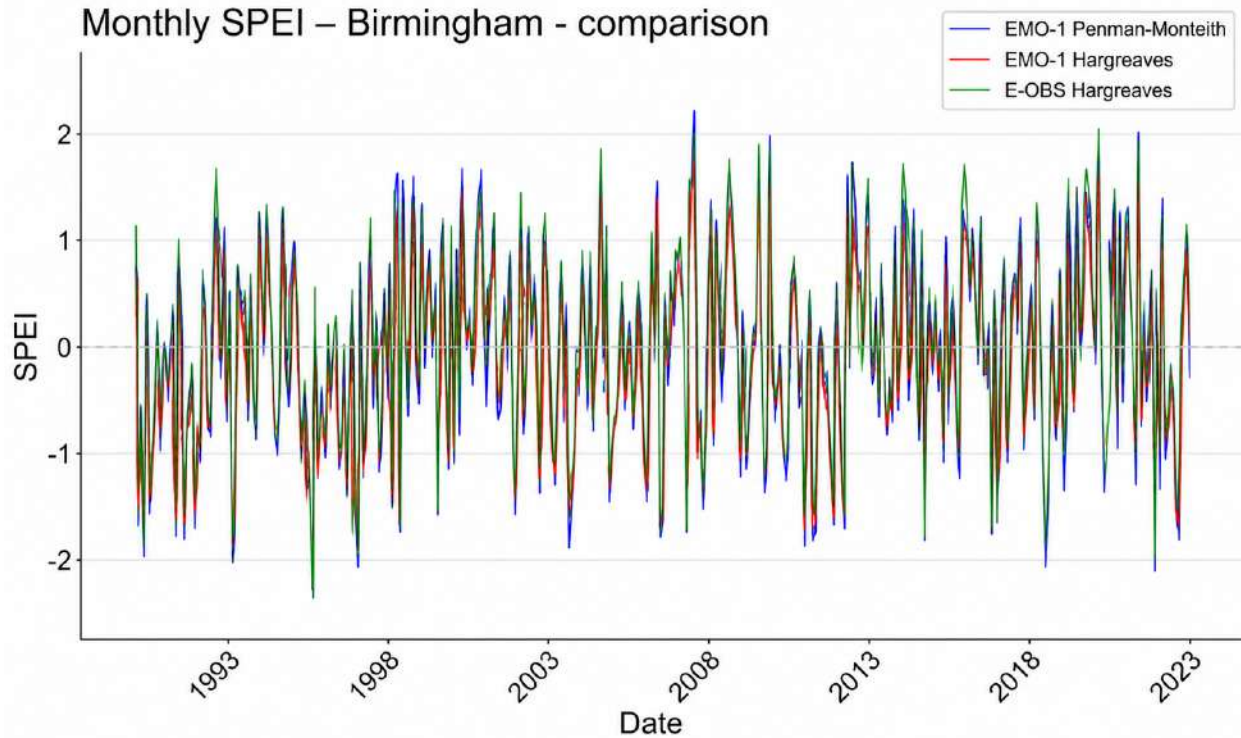
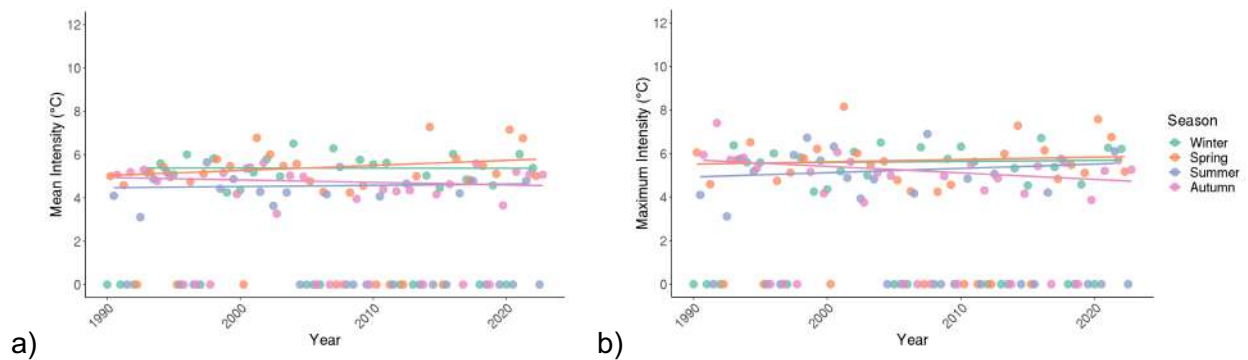


Figure A 38: Temporal comparison of monthly SPEI distributions for the greater CSA Birmingham area based on the EMO-1 Penman–Monteith, EMO-1 Modified Hargreaves, and E-OBS Modified Hargreaves approaches during the reference period 1990–2022.

3.5 Comparative assessment of Heatwave trend

3.5.1 Athens



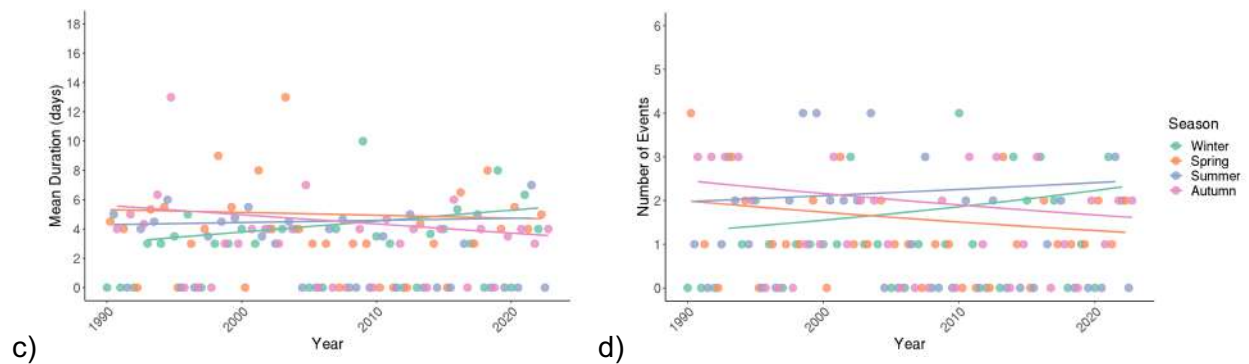


Figure A 39: Temporal distribution of heatwave metrics for the greater CSA Athens area on E-OBS, showing (a) mean cumulative intensity ($^{\circ}\text{C}$), (b) maximum intensity ($^{\circ}\text{C}$), (c) mean duration (days), and (d) mean occurrence of heatwave events for each season during the period 1990–2022. The trend for non-zero values for each season is estimated using linear regression, except for heatwave frequency, where a generalized linear model was applied.

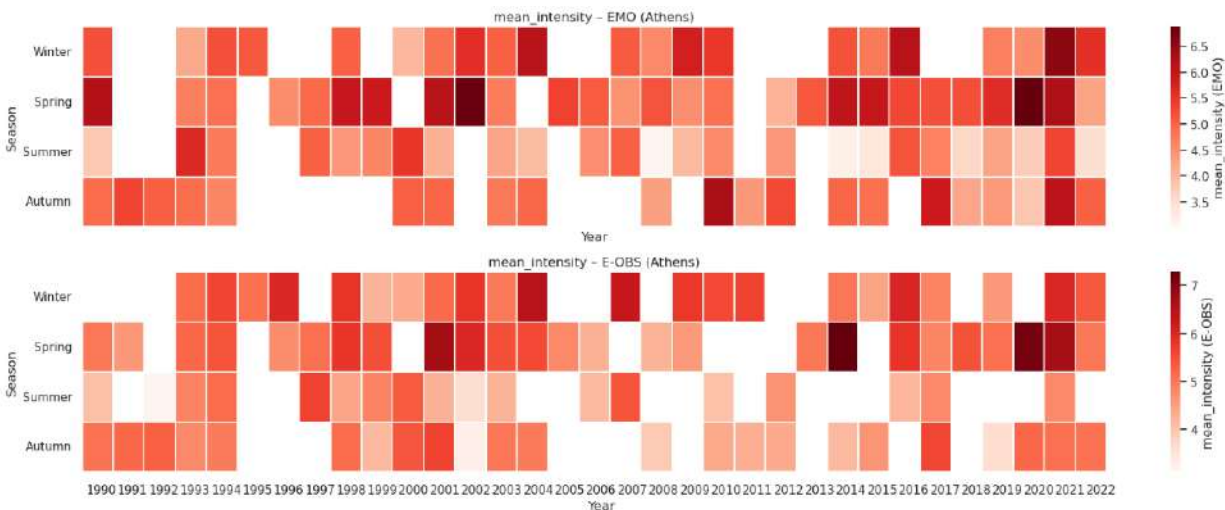


Figure A 40: Comparison of seasonal mean heatwave intensity for the greater CSA Athens area derived from the EMO-1 and E-OBS datasets during the reference period 1990–2022. The figure highlights the temporal variability of heatwave intensity across seasons and illustrates differences in heatwave detection associated with the spatial resolution of the underlying datasets.

Climate hazards indicators. These indicators quantify the physical intensity, frequency, and geographic distribution of a specific hazard.

3.5.2 Heat Magnitude Day

The analysis of heat-related hazards for each CSA is based on the Heat Magnitude Day (HMD, $^{\circ}\text{C}$) index by Zampieri et al. (2017) that slightly modifies the Heat Wave Magnitude Index daily (HWMId) by Russo et al. (2015). HMD is defined as the cumulative maximum temperature exceedances during a heatwave, where a heatwave is commonly defined as days on which the maximum temperature exceeds the long-term 90th percentile for at least three consecutive days.

The composite metric thus quantifies the intensity of extreme heat events and captures the cumulative heat stress over a given period by accounting for the extent to which daily temperatures exceed a defined threshold (typically the 90th percentile). This makes the HMD particularly valuable for assessing impacts on agricultural productivity associated with prolonged and severe heat events (e.g., Zampieri et al., 2017) and potentially other sectors as well. In this deliverable we interpret the HMD output as cumulative intensity of the heatwave events.

For the purposes of the CARMINE project and this Deliverable, a heatwave is defined as a period of at least three consecutive days, allowing 1 day gap, during which the daily maximum temperature exceeds the 90th percentile of a defined reference period (1992–2022). The 90th percentile threshold is calculated using a 5-day moving window, which provides conservative smoothing and increases the robustness of the sample size used for threshold estimation (Brunner and Voigt, 2024). From the detection algorithm, we obtain the number of events (denoted below as occurrence) as well as duration (denoted below as duration) for the whole period 1990–2022. The analysis relies on daily maximum temperature data from the EMO-1 dataset (Gomes et al., 2025).

3.5.3 *Standardized Precipitation Evapotranspiration Index*

The second applied indicator is the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), a widely used indicator for quantifying meteorological drought by incorporating both precipitation and potential evapotranspiration. By accounting for the climatic water balance (precipitation minus potential evapotranspiration), the SPEI enables a multiscale assessment of drought conditions, which is particularly relevant under climate change scenarios marked by rising temperatures and increased evaporative demand. The flexibility of the index across various time scales makes it a robust tool for comprehensive drought monitoring and trend analysis.

Specifically, the SPEI provides insights into:

- a) Drought intensity, where negative SPEI values reflect water deficits; the more negative the value, the more severe the water deficit, either due to low precipitation and/or elevated evapotranspiration. Values ≤ -1 denote drought conditions;
- b) Moisture surpluses, indicated by positive SPEI values, resulting from above-average precipitation and/or reduced evaporative losses. Values ≥ 1 denote very wet conditions;
- c) Drought duration and frequency, through the temporal tracking of negative SPEI values and below -1 , capturing the cumulative impact of sustained precipitation deficits and high atmospheric demand.

For the CARMINE CSAs the SPEI has been computed on a monthly basis (hereafter SPEI-1), using a reference period from 1992 to 2022. Values of $\text{SPEI-1} \leq -1$ are classified as drought conditions, while values of $\text{SPEI-1} \geq 1$ indicate wet conditions, corresponding to deviations in the climatic water balance of one standard deviation from the long-term mean. The analysis is based on daily precipitation data from the EMO-1 dataset.

The daily potential evapotranspiration (PET) is calculated using the Penman-Monteith equation, driven by meteorological variables also derived from EMO-1. This method integrates net radiation, aerodynamic and evaporative demand, the slope of the saturation vapour pressure curve, and the psychrometric constant to estimate water loss from a reference vegetation surface. This combined approach supports a robust and physically grounded assessment of meteorological drought across diverse climatic and geographical settings. The calculation of the PET following the Penman-Monteith equation has taken place with the LISFLOOD hydrological model (European Commission 2026).

For comparison reasons, a further approach has been used for the calculation of PET, namely the simpler and less variable-intensive method by Hargreaves (Hargreaves and Samani, 1985). The original Hargreaves equation was developed as a simpler alternative to more data-intensive models such as the Penman–Monteith method. While the Penman–Monteith approach requires multiple variables, the Hargreaves approach mainly relies on maximum and minimum air temperature, as well as extraterrestrial radiation. The Modified Hargreaves approach improves the original equation by incorporating additional correction factors as calibration coefficients to increase accuracy under different climatic conditions. The main advantage of the Modified Hargreaves approach is its balance between simplicity and reliability. It requires fewer input variables than physically based models, making it more practical and appropriate for large-scale studies. However, the model may not fully capture real environmental conditions due to its fewer input variables, which is why the Penman-Monteith method is generally recommended, provided that accurate weather stations are available (Droogers & Allen 2002).

Nevertheless, the two approaches for the calculation of PET are used to assess potential differences connected with the different approaches. However, the aim is not to perform an assessment exercise of the used datasets but only to describe the outputs and observed differences. These are presented in the Annex section 9.3: SPEI based on Modified Hargreaves, for total drought (see section 9.3.1) and wetness characteristics (see section 9.3.2) for the respective CSAs of interest, as well as their seasonal drought (see section 9.3.3) and wetness maps (see section: 9.4.4). Overall, the results show a reasonable agreement between the two methods, which was also observed by Droogers & Allen (2002). However, there are also differences, and the modified approach often shows less spatial variability. When comparing the total drought maps, it is striking that in several cases the Penman–Monteith method identifies hotspots which were not detected by the Modified Hargreaves approach. The time series plots also generally show a smaller range and fewer extreme years. In summary, these results justify the use of the more complex Penman–Monteith method to capture greater spatial variability.

In addition, the Modified Hargreaves method was also applied to the SPEI calculation with lower-resolution E-OBS data to evaluate whether the spatial resolution is related to the overall low trends in the temporal characteristics, which were observed in the results of the SPEI based on the Penman–Monteith approach. The results are presented in the Annex section 9.4: SPEI based on Modified Hargreaves and E-OBS Data, for total drought (see section 9.4.1) and wetness characteristics (see section 9.4.2) for the respective CSAs of interest, as well as their seasonal drought (see section 9.4.3) and wetness maps (see section: 9.4.4). A comparative analysis of the

temporal SPEI distributions derived from the three approaches (EMO-1 Penman–Monteith, EMO-1 Modified Hargreaves, and E-OBS Modified Hargreaves) showed that the main temporal variability patterns remain broadly consistent across datasets and methods. In particular, major dry and wet periods are generally captured simultaneously by all approaches, suggesting that the temporal evolution of SPEI is relatively robust with respect to spatial resolution changes. At the same time, the E-OBS-based results do not exhibit a systematically reduced variability range compared to the higher-resolution EMO-1 data, indicating that the observed differences are likely related not only to spatial resolution, but also to the combined effects of the input dataset characteristics and PET formulation. The comparative temporal analyses are presented in Annex section 9.5 for Athens (see section 9.5.1), Barcelona (see section 9.5.2), and Birmingham (see section 9.5.3).

3.5.4 Combined Stress Index

The Combined Stress Index (CSI) is employed to assess the cumulative impact of multiple environmental stressors, including temperature extremes, precipitation deficits, and water availability, on ecosystems, agricultural systems, and human settlements. The CSI is a statistical model that integrates calibrated indicators of heat and hydrological stress into a single composite index, providing a multidimensional representation of environmental stress conditions. By combining these variables, the CSI delivers a more holistic evaluation of climate-related pressures compared to single-variable indices, enabling a deeper understanding of compound and interacting risks. This makes it particularly valuable for climate impact assessments, agricultural risk planning, and resource management strategies under future climate variability and extremes. The CSI has been widely applied to quantify the impacts of climate anomalies in the present-day climate (Zampieri et al., 2017, 2018, 2019b) and has also been used in the context of seasonal forecasting (Ceglar et al., 2018) and economic modelling (Chatzopoulos et al., 2019).

For the CARMINE CSAs, the CSI is computed by integrating the HMD index and the SPEI-1, providing a measure of the intensity of compound events, such as joint heat and drought stress, or heat and wet conditions. To ensure comparability across variables and locations, all input metrics were standardized using z-scores. Subsequently, a Principal Component Analysis (PCA) was conducted independently for each CSA. The first principal component, which captures the dominant mode of joint variability in heat and drought conditions, was extracted and used as the CSI. The resulting CSI values represent annual accumulations of compound stress events, summarizing the combined influence of heatwaves and drought or heatwaves and wet events on each CSA. For visual analysis, only years with extreme CSI values, defined as those exceeding 1 standard deviation, were selected, and their spatial mean values were used to highlight high-impact areas of environmental stress.

3.5.5 Annual Probability Estimation

The visualisation of “hotspot” areas is based on the annual probability of occurrence of heatwaves, droughts and wet events in the period 1990–2022 for each grid point within each greater CSA area. The annual probability of extreme events refers to the likelihood that an extreme event occurred during a given period and at a specific location (grid box). Here, it is expressed as a value between 0 and 1, where 0 means that the event has never occurred and 1

that the extreme event has been observed in every year of the study period. The classes used are: 0-0.20 very low probability, 0.21-0.40 low probability, 0.41-0.60 moderate probability, 0.61-0.80 high probability and 0.81-1 very high probability. This metric allows for a spatial assessment of event likelihood, and it supports the identification of hotspot regions. As defined earlier, a heatwave is a period of at least three consecutive days during which the daily maximum temperature exceeds the 90th percentile of a defined reference period, here 1992–2022. Droughts are identified by a SPEI-1 ≤ -1 , while wet conditions correspond to SPEI-1 ≥ 1 .

3.6 Heatwaves

The maps presented in this section illustrate the spatial distribution of key heatwave characteristics, namely mean cumulative intensity from HMD ($^{\circ}\text{C}$), mean duration in days, and mean annual occurrence, calculated over the full study period 1990–2022 for each grid point within the respective CSAs (Figure 6, Figure 8, Figure 10, Figure 12, Figure 14, Figure 16, and Figure 18). In addition, the temporal figures are based on spatial aggregations over the greater areas surrounding the CARMINE CSAs and display the seasonal mean ($^{\circ}\text{C}$) and maximum intensity (mean over the peak intensities of all events in $^{\circ}\text{C}$), as well as mean duration in days and number of identified heat events for all relevant CSAs (Figure 7, Figure 9, Figure 11, Figure 13, Figure 15, Figure 17, and Figure 19). Trend lines are presented for each season and are estimated for non-zero values using linear regression, except for heatwave frequency, where a generalized linear model was applied. To further assess the robustness of the heatwave results and address potential uncertainties related to the underlying climate datasets, an additional comparison was performed using the lower-resolution E-OBS dataset alongside the EMO-1 data, while maintaining the same heatwave detection algorithm for all CSAs to ensure a harmonised methodological approach. The comparison focuses on the temporal evolution and spatial distribution of the main heatwave characteristics across the selected CSAs, allowing an evaluation of the consistency of the identified patterns and the potential influence of dataset resolution on the derived indicators. The overall temporal behaviour and major heatwave events remain generally comparable between the datasets, as shown by the comparative analyses reported in the Annex section 9.6.

3.6.1 CSA Prague

The map of mean heatwave cumulative intensity for the greater area surrounding CSA Prague (Figure 6a) indicates that the most intense events are concentrated in the northern and western sectors of the region. The city of Prague itself lies within a moderately high-intensity zone, with a mean HMD value around 1.8°C . This relatively uniform yet elevated cumulative intensity suggests a broad spatial exposure to heat stress across the metropolitan area. The mean duration of heatwaves (Figure 6b) shows that areas surrounding Prague tend to experience slightly longer events, with values approaching or exceeding 4.5 days, compared to the urban core and peripheral zones. However, the overall variability in duration is limited, deviating by no more than 0.5 days, indicating a fairly homogeneous spatial distribution. Regarding heatwaves frequency (Figure 6c), the number of events ranges between approximately 3.5 to 4.5 per year. The spatial

pattern highlights a concentration of more frequent events in the north-eastern quadrant and along the western edge, whereas Prague itself is less frequently affected by comparison.

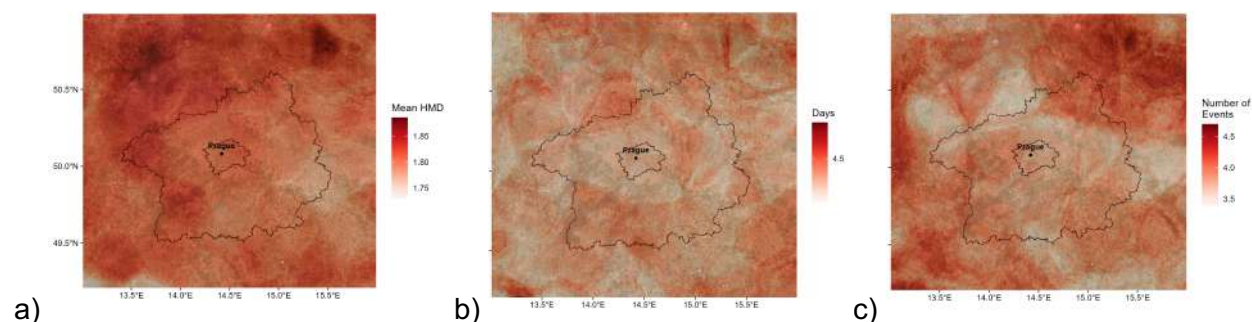
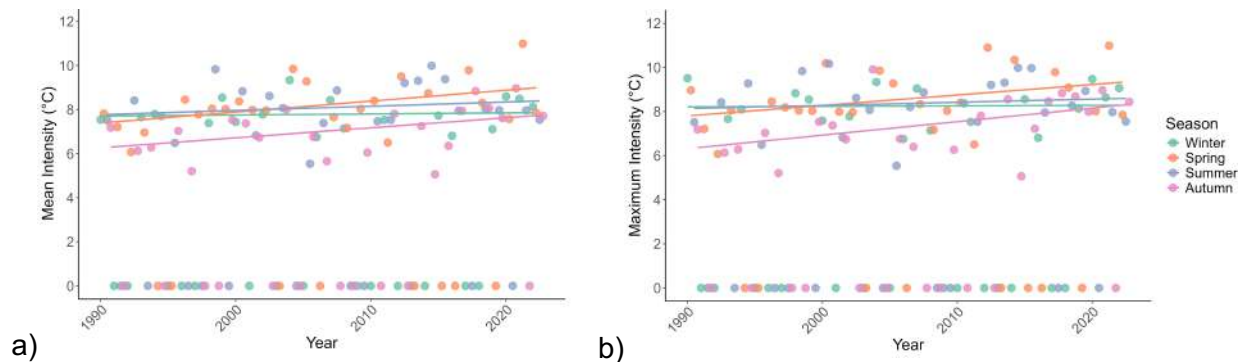


Figure 6: Spatial distribution of heatwave metrics for the greater CSA Prague area, showing (a) mean annual cumulative intensity ($^{\circ}\text{C}$), (b) mean annual duration (days), and (c) mean annual occurrence of heatwave events for the years 1990–2022.

The temporal evolution of mean and maximum heatwave intensity in the greater CSA Prague area (Figure 7a and b) reveals a clear seasonal pattern, with higher intensity values predominantly observed during spring, summer and autumn, although notable events also occur also in winter. While many seasons record no heatwave events (i.e., zero intensity), those with heatwaves typically exhibit mean and maximum intensities ranging between 5°C and 10°C , with some maximum values exceeding 10°C . These extreme maximum intensities become higher over the course of the study period for all seasons. The mean duration of heatwaves (Figure 7c) similarly shows a marginal increase, with most events lasting between three and five days. Many seasons show no heatwave days at various parts of the study period. The winter of 2002 stands out as an extreme outlier, with an average duration of 16 days, followed by spring 2009 with 10 days. Overall, seasonal differences in duration remain relatively subdued. The annual number of heatwave events (Figure 7d) also exhibits a slightly increasing trend throughout the study period. In most years, one or no events are recorded per season, with occasional peaks of up to three events. Notably, winter 1998 and summer 2019 each recorded four heatwave events, marking the highest seasonal frequencies observed.



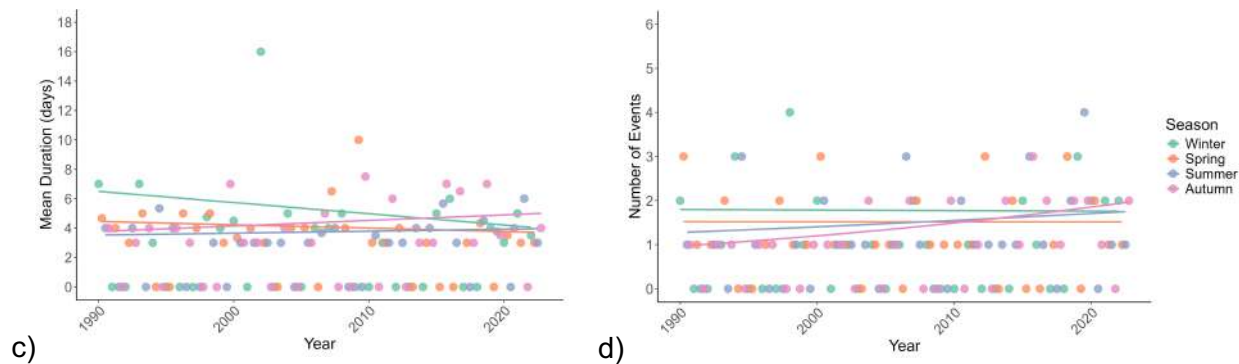


Figure 7: Temporal distribution of heatwave metrics for the greater CSA Prague area, showing (a) mean cumulative intensity ($^{\circ}\text{C}$), (b) maximum intensity ($^{\circ}\text{C}$), (c) mean duration (days), and (d) mean occurrence of heatwave events for each season during the period 1990–2022. The trend for non-zero values for each season is estimated using linear regression, except for heatwave frequency, where a generalized linear model was applied.

3.6.2 CSA Leipzig

The map of mean heatwave cumulative intensity for the greater CSA Leipzig area (Figure 8a) identifies the western edge of the study area, particularly the Harz Mountains, as the region experiencing the most intense events, with HMD values reaching up to 1.95°C . In contrast, the south-eastern half of the CSA generally shows lower intensity levels, except for the far south-eastern corner. The city of Leipzig itself is situated within an area of moderate cumulative intensity. The heatwave duration map (Figure 8b) indicates slightly longer durations in the northern regions of the CSA, including around Leipzig, compared to the south. Specific zones of elevated duration values are observed north of Leipzig, in the south-east, and again in parts of the Harz Mountains. Nevertheless, the overall range of variability in mean duration remains modest, generally less than one full day. Regarding the annual heatwave frequency (Figure 8c), the highest number of events, averaging 4.5 per year, is observed in the Harz Mountains and the south-western sector of the CSA. In contrast, Leipzig lies within a region characterized by lower event frequency, averaging around 3.5 heatwave occurrences per year, placing it in the lower half of the spatial distribution.

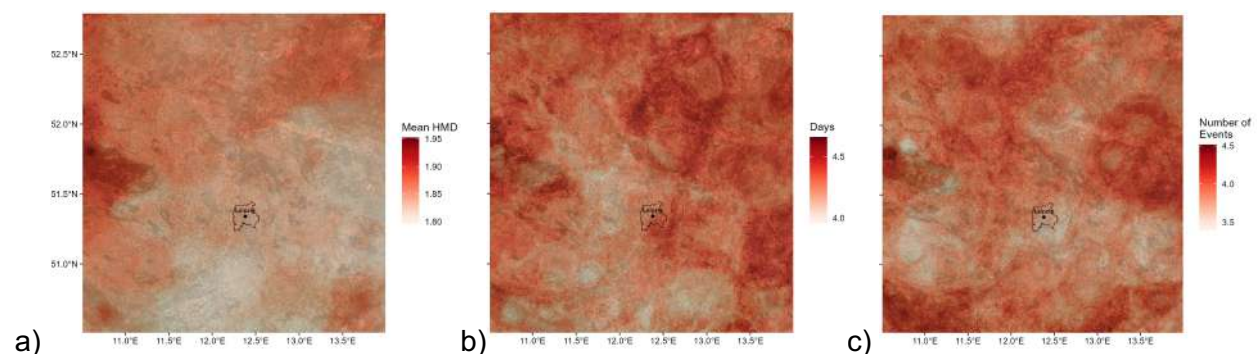


Figure 8: Spatial distribution of heatwave metrics for the greater CSA Leipzig area, showing (a) mean annual cumulative intensity ($^{\circ}\text{C}$), (b) mean annual duration (days), and (c) mean annual occurrence of heatwave events for the years 1990–2022.

The temporal evolution of mean cumulative and maximum heatwave intensity in the greater CSA Leipzig (Figure 9a and b) reveals an increase for both metrics across the study period. Notably,

spring 1996 and summer 2002 stand out as early-season extremes, while summer 2016 and spring 2021 represent more recent high-intensity events, each with values exceeding 10 °C. These extreme intensities become more frequent in the later years, particularly in the maximum intensity series, indicating a strengthening of heatwave severity over time. The mean duration of heatwaves (Figure 9c) also shows a slight increase, with most events persisting for three to five days. However, several years still exhibit no heatwave activity in contrast to the later part of the study period. Two notable outliers, summer 1994 and winter 2002, record durations of ten days or more, while spring and summer seasons are more frequently associated with longer-lasting events. The seasonal frequency of heatwave events (Figure 9d) similarly demonstrates a slight increase throughout the study period. Occasional peaks of up to three or four events occur, particularly in the later part of the series after 2010.

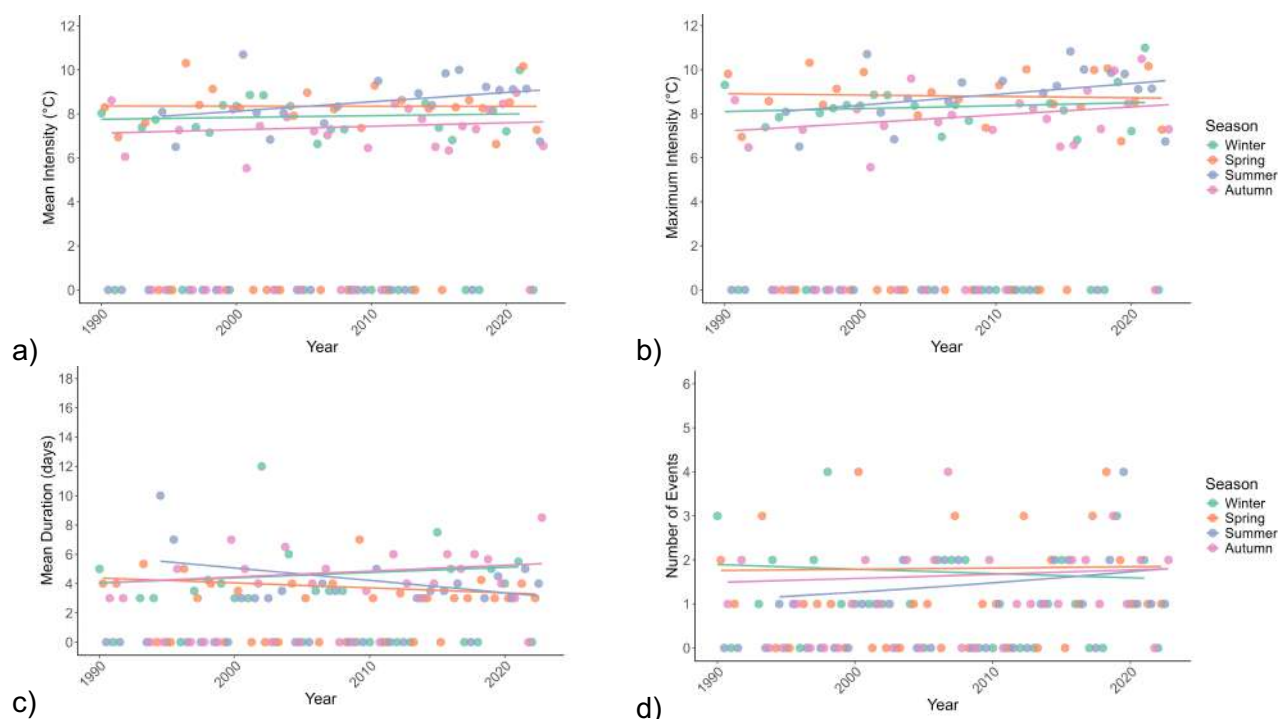


Figure 9: Temporal distribution of heatwave metrics for the greater CSA Leipzig area, showing (a) mean cumulative intensity (°C), (b) maximum intensity (°C), (c) mean duration (days), and (d) mean occurrence of heatwave events for each season during the period 1990–2022. The trend for non-zero values for each season is estimated using linear regression, except for heatwave frequency, where a generalized linear model was applied.

3.6.3 CSA Athens

The map of mean heatwave cumulative intensity for the greater CSA Athens area (Figure 10a) highlights far from Athens, in the south-western Peloponnese, as experiencing the most intense events, with HMD values exceeding 2.1 °C. Additional elevated values are observed along northern coastal areas, while most of the region, including the urban core of Athens, falls within the lower range of the distribution. In contrast, the mean heatwave duration (Figure 10b) illustrates a more uniform exposure to prolonged events across much of the greater area. Particularly along the mountain ranges in the south-east, durations exceed five days, suggesting enhanced persistence of heat extremes in these zones. The shortest durations, around four days, are found

in the northern island regions, indicating spatial variability in event persistence. Regarding mean annual heatwave occurrence (Figure 10c), the region overall experiences frequently events, with values reaching up to five events per year. Areas with lower occurrence rates, typically below 3.5 events, are concentrated far to the northern and southwestern edges, suggesting localized variability in the frequency of extreme heat episodes.

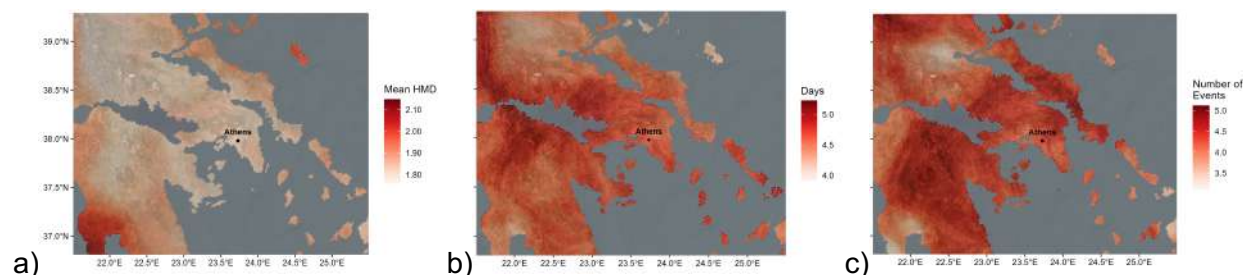
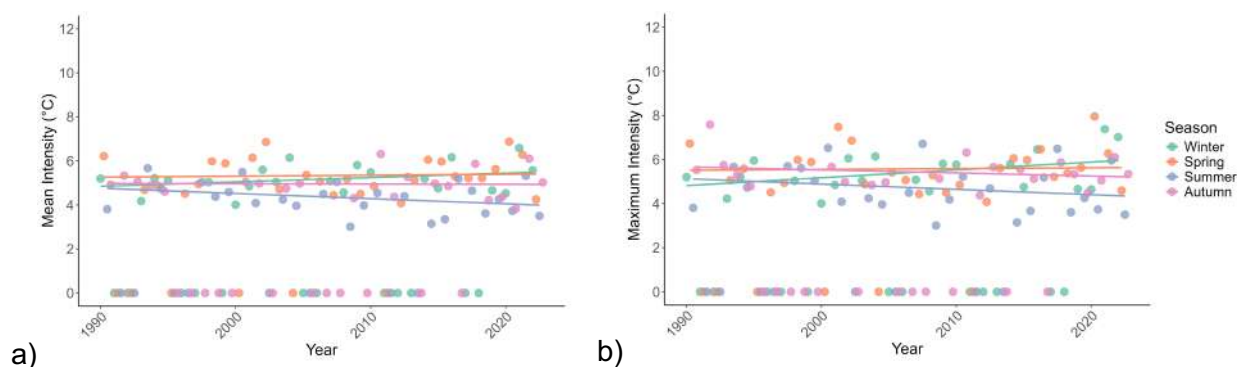


Figure 10: Spatial distribution of heatwave metrics for the greater CSA Athens area, showing (a) mean annual cumulative intensity ($^{\circ}\text{C}$), (b) mean annual duration (days), and (c) mean annual occurrence of heatwave events for the years 1990–2022.

The temporal evolution of mean heatwave cumulative intensity in the greater CSA Athens (Figure 11a) reveals a relatively stable range, with values fluctuating between 3°C and 7°C across the study period. Although the stable range in terms of intensity, there is a notable increase in the number of events in all seasons, indicating a gradual increase in frequency. A similar pattern emerges for the maximum heatwave intensity (Figure 11b), where the highest recorded value, approaching 8°C , was observed in spring 2020. This metric suggests that single-day intensities are becoming more extreme, particularly in recent years. The mean duration of heatwaves (Figure 11c) shows a slight increase, with most events lasting between three and seven days. Four distinct outlier events reached durations of at least ten days, with the winter of 2007 standing out with the maximum recorded duration of 14 days. The annual number of heatwave events (Figure 11d) also displays a modest increase. Most years recorded one event per season, while some had two or three. Notably, the summers of 2007 and 2012 recorded a total of four heatwave events each. Importantly, all metrics converge to show that in the last four to ten years of the study period, every season experienced at least one heatwave event, underscoring also a recent intensification in frequency and persistence of extreme heat events in the greater Athens region.



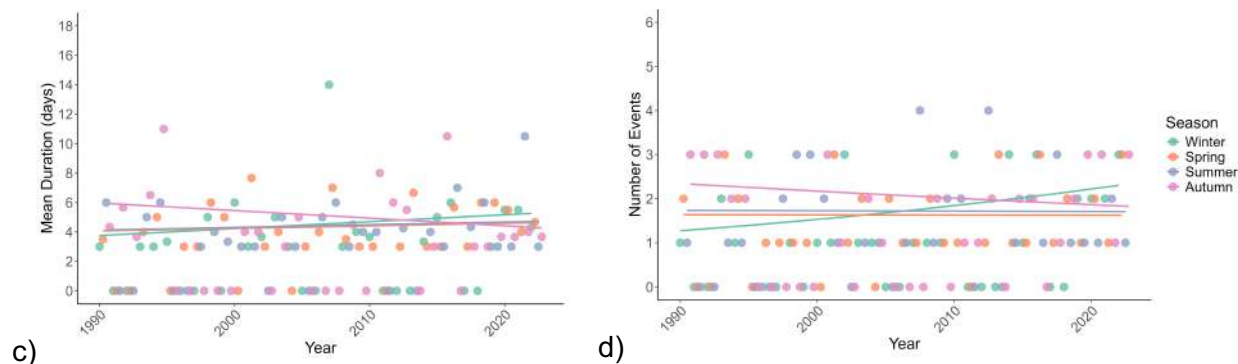


Figure 11: Temporal distribution of heatwave metrics for the greater CSA Athens area, showing (a) mean cumulative intensity ($^{\circ}\text{C}$), (b) maximum intensity ($^{\circ}\text{C}$), (c) mean duration (days), and (d) mean occurrence of heatwave events for each season during the period 1990–2022. The trend for non-zero values for each season is estimated using linear regression, except for heatwave frequency, where a generalized linear model was applied.

Additional analyses based on the lower-resolution E-OBS dataset were performed to further evaluate the observed temporal trends and address potential uncertainties related to the underlying climate data. The comparison was specifically carried out to assess the apparent very small and at the same time decreasing trends in summer cumulative and maximum heatwave intensity observed for the Athens CSA in the EMO-1 results (Figure 11a, Figure 11b). The comparative assessment indicates that these linear trends are not statistically significant and should therefore be interpreted with caution and cannot be considered as an actual and worth mentioning decreasing trend. Moreover, the E-OBS results also show a relatively steady temporal behaviour during the summer season, without an increasing or decreasing trend in heatwave intensity, in agreement with the EMO-1 results. At the same time, the comparison highlights notable differences in heatwave detection between the two datasets. In particular, the E-OBS dataset identifies fewer heatwave events, especially during summer and for lower-intensity events (see section 9.6.1). This behaviour likely reflects the coarser spatial resolution of E-OBS, which tends to smooth local-scale thermal variability and reduce the detectability of spatially confined heatwave events. This effect is particularly relevant for the Athens CSA, where heatwave intensity and spatial extent are strongly influenced by localized climatic conditions, coastal interactions, and complex topography. As a result, some localized heatwave events captured by the higher-resolution EMO-1 dataset may not be fully represented in the coarser E-OBS data.

3.6.4 CSA Barcelona

The map of mean annual heatwave cumulative intensity for the greater CSA Barcelona area (Figure 12a) highlights the coastal zones as experiencing the most intense heat events, with HMD values reaching approximately 2.2°C . Notable hotspots are located west of and in proximity to the city of Barcelona, indicating a strong influence of coastal climatology on heatwave severity in the region. In terms of mean heatwave duration (Figure 12b), the most pronounced hotspot appears around the urban core of Barcelona, where events persist for up to 5.5 days on average. Additional zones of prolonged heatwave duration are observed north of the CSA, suggesting regional topographic or land-surface effects contributing to the persistence of extreme heat. Conversely, the mean annual heatwave occurrence (Figure 12c) reveals a different spatial pattern: the fewest events, with around three per year, are concentrated in the southern coastal areas, including Barcelona. In contrast, the remainder of the greater CSA area experiences

significantly higher frequencies, with more than 4.5 events per year, indicating a spatial decoupling between frequency and cumulative intensity/duration patterns within the region.

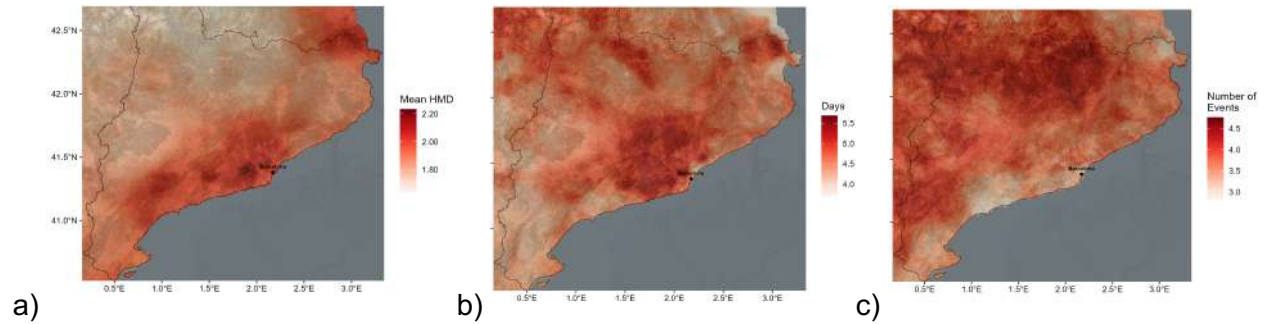
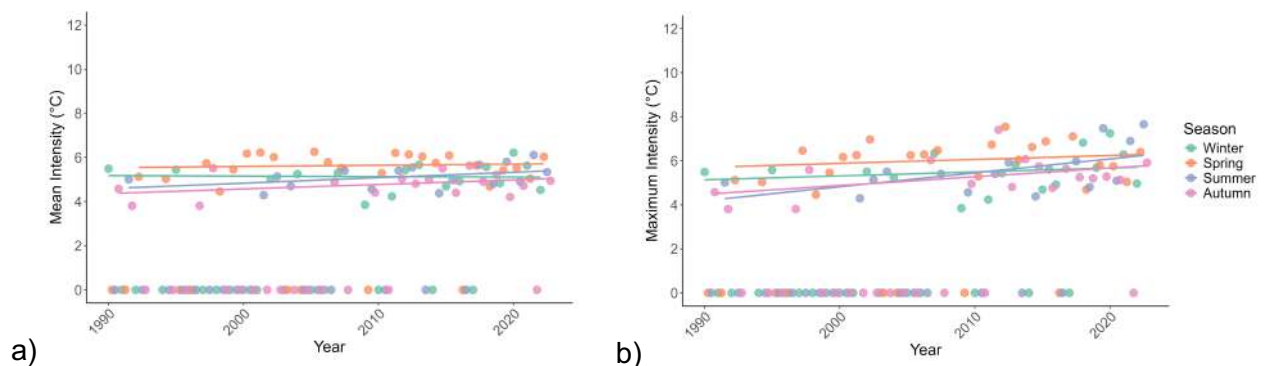


Figure 12: Spatial distribution of heatwave metrics for the greater CSA Barcelona area, showing (a) mean annual cumulative intensity ($^{\circ}\text{C}$), (b) mean annual duration (days), and (c) mean annual occurrence of heatwave events for the years 1990–2022.

The temporal evolution of mean cumulative heatwave intensity in the greater CSA Barcelona area (Figure 13a) reveals a relatively stable intensity range, with most events registering between 4°C and 6°C . However, the frequency of heatwave seasons increases over time. While numerous seasons at the beginning of the study period show no heatwave activity, such instances become increasingly rare in the later years, resulting in an overall increase in seasonal heatwave occurrence. A more pronounced increase is observed in the maximum heatwave intensity (Figure 13b), which reaches values approaching 8°C . These high values are more frequently recorded toward the end of the study period, underscoring a growing intensity of peak events. The mean duration of heatwaves (Figure 13c) also displays a clear increase, with longer-lasting events concentrated in the second half of the study period. During this time, HMD values between 8°C and 10°C are recorded repeatedly, particularly in spring and summer, indicating a shift toward more intense heat events. This pattern is mirrored in the seasonal number of heatwave events (Figure 13d), which also shows a notable increase over time. While zero-event seasons are common in the early years of the study period, they become infrequent later. In the second half of the period, four to five events per season are observed in autumn 2011, spring 2017, and summer 2022, highlighting a significant escalation in event frequency and clustering.



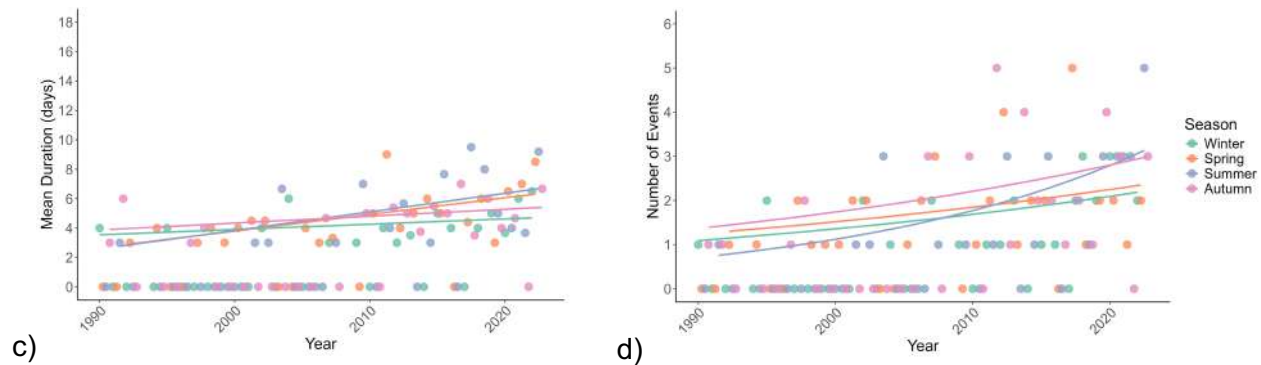


Figure 13: Temporal distribution of heatwave metrics for the greater CSA Barcelona area, showing (a) mean cumulative intensity ($^{\circ}\text{C}$), (b) maximum intensity ($^{\circ}\text{C}$), (c) mean duration (days), and (d) mean occurrence of heatwave events for each season during the period 1990–2022. The trend for non-zero values for each season is estimated using linear regression, except for heatwave frequency, where a generalized linear model was applied.

3.6.5 CSA Bologna

The map of mean heatwave cumulative intensity for the greater CSA Bologna area (Figure 14a) indicates that the most intense events occur along sections of the farther located western and eastern coastal areas, where HMD values approach 2.1°C . In contrast, the remainder of the region is generally exposed to lower intensity levels, with HMD values decreasing to approximately 1.7°C , reflecting a moderate spatial gradient in heatwave severity across the greater CSA area. Regarding mean heatwave duration (Figure 14b), the most prolonged events, lasting up to 5.5 days on average, are found east of CSA Bologna, including a notable coastal hotspot where duration values peak. In comparison, the shortest durations, around 4 days, occur in the south-eastern part of the area. In contrast to intensity and duration, the mean annual occurrence of heatwaves (Figure 14c) is relatively high throughout much of the greater CSA area, with 4–4.5 five events per year recorded in Bologna.

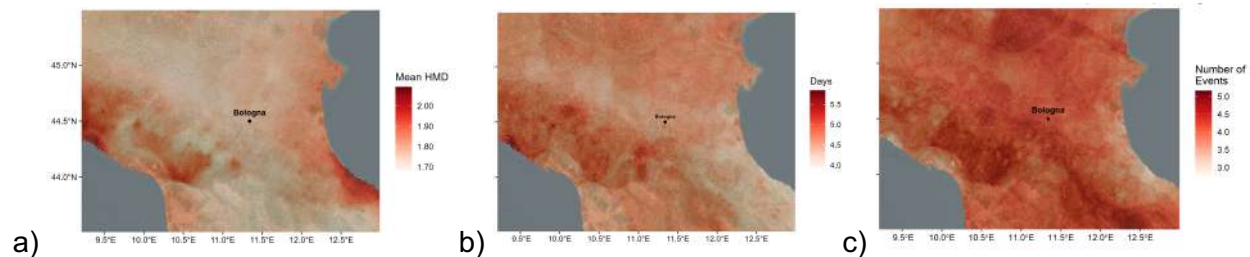


Figure 14: Spatial distribution of heatwave metrics for the greater CSA Bologna area, showing (a) mean annual cumulative intensity ($^{\circ}\text{C}$), (b) mean annual duration (days), and (c) mean annual occurrence of heatwave events for the years 1990–2022.

The temporal evolution of mean cumulative and maximum heatwave intensity in the greater CSA Bologna area (Figure 15a and b) reveals a gradual intensification over time, with notably higher intensity values emerging toward the end of the study period. Peak mean intensity values, approaching 8°C , are recorded in the winter of 2021, while similarly elevated maximum intensities occur in both winter 2019 and winter 2021. Aside from winter extremes, spring seasons also frequently appear in the upper range of intensity, indicating a broadening seasonal window for heatwave conditions. The increasing presence of heatwaves in later years, replacing previously common zero-event seasons, reflects a clear increase in frequency and intensity. The mean

heatwave duration (Figure 15c) similarly shows a distinct increase, with events becoming longer and more persistent in recent years. While most events range between three and six days, the summer of 2022 stands out with an exceptional duration of 22 days. Several other outlier seasons, particularly in spring and summer, exceed 10 days, underscoring the potential for prolonged heat stress events. A clear reduction in heatwave-free seasons is observed in the second half of the study period. A comparable pattern is seen in the annual number of heatwave events (Figure 15d), which also shows a clear increase over time. While zero-event seasons are prevalent in the early years, they become infrequent after the mid-2000s. In the second half of the period, seasons with four or five events occur multiple times, notably in summer 2015, summer 2022, and winter 2022. The maximum number of six heatwave events is recorded in spring 2007, marking the most active heatwave season of the entire study period for the greater region around CSA Bologna.

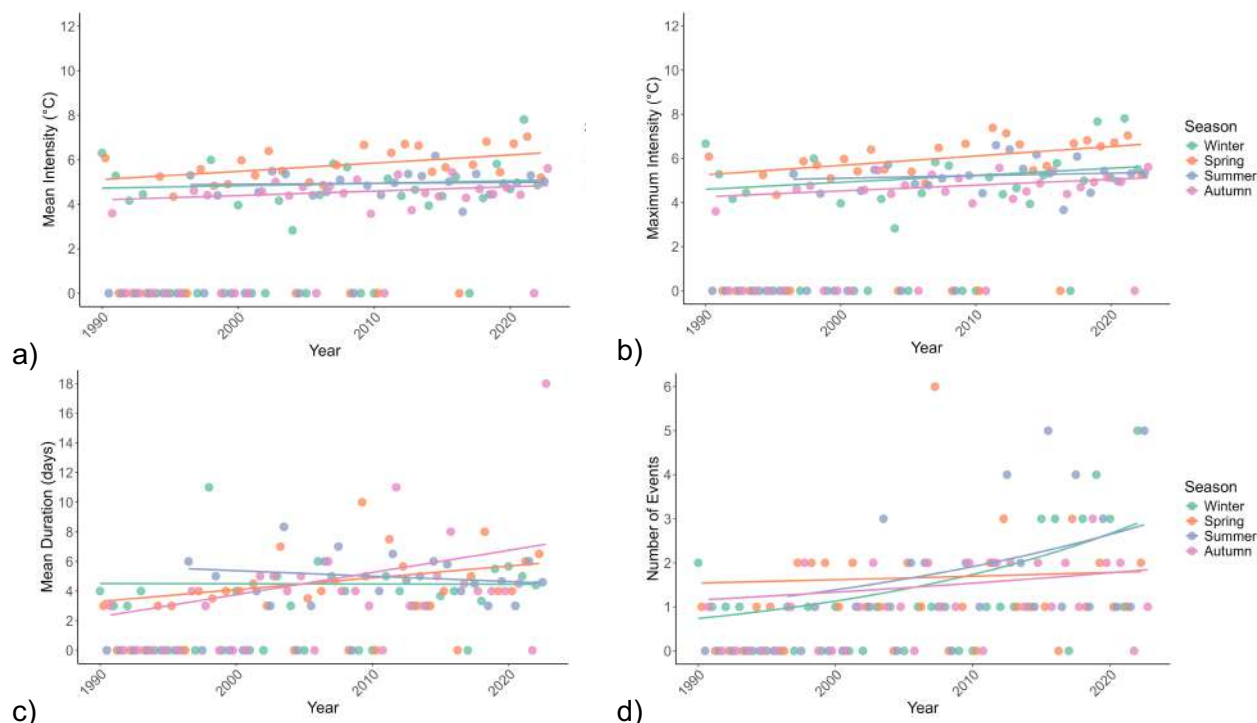


Figure 15: Temporal distribution of heatwave metrics for the greater CSA Bologna area, showing (a) mean cumulative intensity ($^{\circ}\text{C}$), (b) maximum intensity ($^{\circ}\text{C}$), (c) mean duration (days), and (d) mean occurrence of heatwave events for each season during the period 1990–2022. The trend for non-zero values for each season is estimated using linear regression, except for heatwave frequency, where a generalized linear model was applied.

3.6.6 CSA Brasov

The map of mean heatwave cumulative intensity for the greater CSA Brasov area (Figure 16a) shows that the most intense heatwave events are concentrated in the far north-eastern and eastern parts of the area, where HMD values reach approximately 1.9°C . The lowest cumulative intensities across the whole area, around 1.7°C , are observed in the area surrounding the city of Brasov, indicating relatively lower cumulative heat stress in the urban core. In contrast, the map of mean heatwave duration (Figure 16b) reveals that the longest-lasting heatwaves, with durations of up to five days, occur precisely in the central region around Brasov. Regarding mean annual heatwave occurrence (Figure 16c), the lowest frequencies, fewer than four events per

year, are again centred around Brasov and extend into the south-eastern portion of the CSA. Conversely, the highest occurrence rates, reaching up to five events annually, are found south of Brasov, particularly in areas near the Fagaras Mountains, reflecting localized climatic influences tied to topography and air mass interactions.

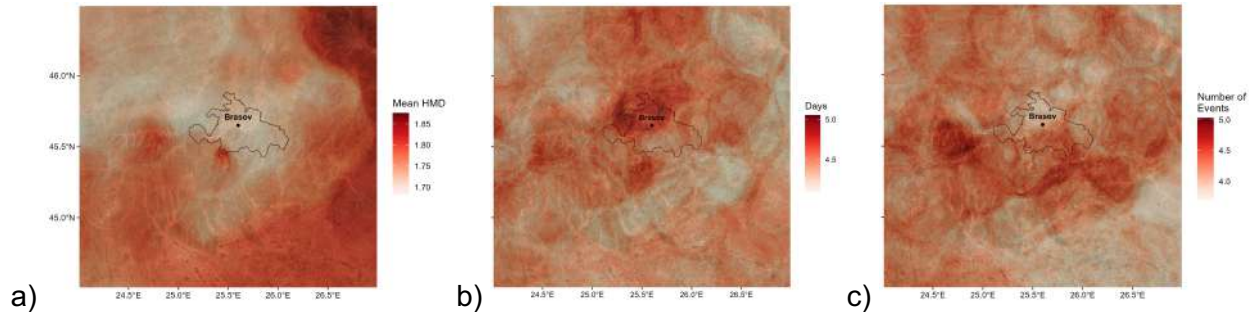
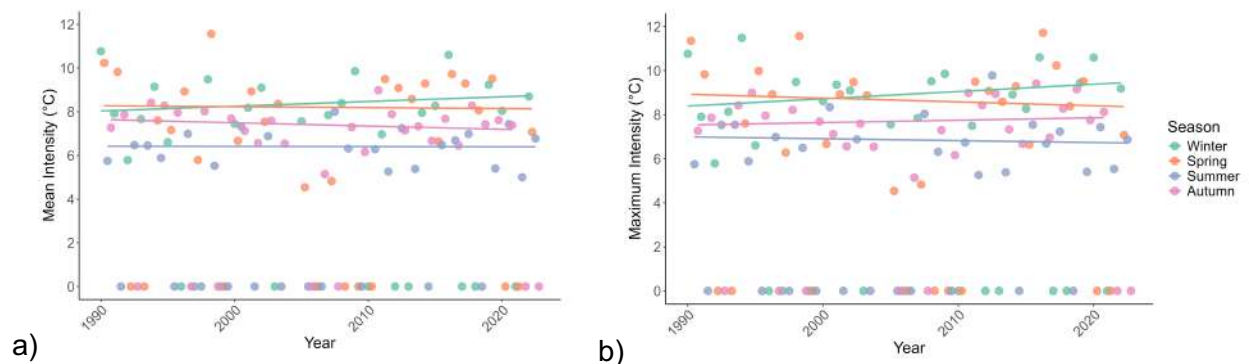


Figure 16: Spatial distribution of heatwave metrics for the greater CSA Brasov area, showing (a) mean annual cumulative intensity ($^{\circ}\text{C}$), (b) mean annual duration (days), and (c) mean annual occurrence of heatwave events for the years 1990–2022.

The temporal evolution of mean cumulative and maximum heatwave intensity in the greater CSA Brasov area (Figure 17a and b) displays a wide range of values, spanning from approximately 4°C to over 12°C , indicating substantial interannual and seasonal variability in heatwave severity. The highest mean intensity is recorded in spring 1998, reaching 11.5°C , while the maximum single-event intensity peaks at 11.7°C in spring 2016. Despite these extremes, both indicators show a rather stable evolution over the study period, likely driven by the clustering of high-intensity events that occurred in the early years of the record. The mean heatwave duration (Figure 17c) generally ranges between three to six days, with multiple seasons without any events (i.e., zero duration). Several outliers, however, show durations exceeding ten days, including the longest event of the series in autumn 2019, which lasted 11 days. While the overall increase is marginal, there is a tendency toward longer durations in the latter half of the study period. A similar temporal dynamic is observed in the seasonal numbers of heatwave events (Figure 17d). Most seasons are characterized by one to two events, with numerous zero-event seasons in the early years. In the second half of the study period, the number of events per season increases slightly, with more frequent occurrences of three events, and occasional spikes up to five events. The maximum number of six events is observed in summer 2012, marking the most active heatwave season in the greater CSA Brasov area.



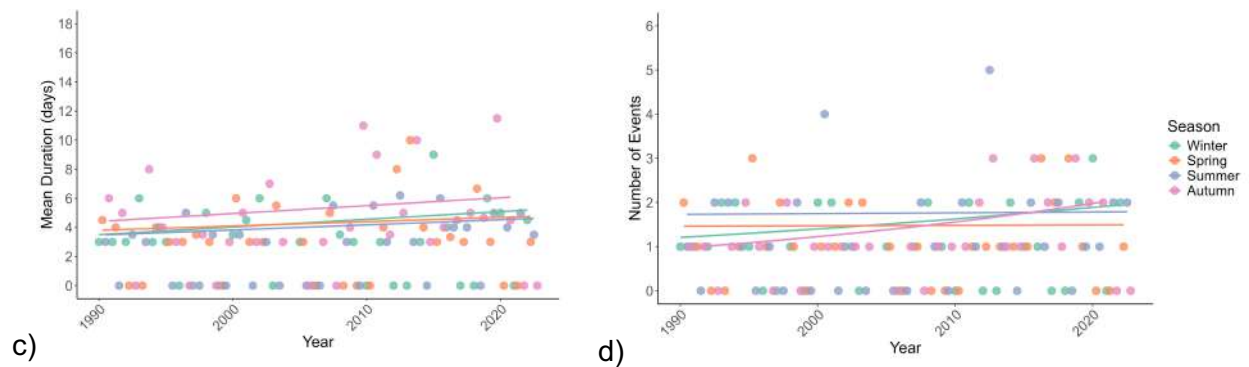


Figure 17: Temporal distribution of heatwave metrics for the greater CSA Brasov area, showing (a) mean cumulative intensity ($^{\circ}\text{C}$), (b) maximum intensity ($^{\circ}\text{C}$), (c) mean duration (days), and (d) mean occurrence of heatwave events for each season during the period 1990–2022. The trend for non-zero values for each season is estimated using linear regression, except for heatwave frequency, where a generalized linear model was applied.

3.6.7 CSA Birmingham

The map of mean heatwave cumulative intensity for the wide area around the Birmingham CSA (Figure 18a) reveals that the highest values occur far from the Birmingham CSA. Around the city of Birmingham, the HMD values remain relatively uniform, clustering around 2°C , suggesting widespread heatwave conditions. In terms of mean heatwave duration (Figure 18b), for the Birmingham CSA values range between 4 and 4.5 days. The pattern for mean annual heatwave occurrence (Figure 18c) shows more frequent heatwaves across the inland areas surrounding and across the Birmingham CSA, with annual occurrence values exceeding 4 events, highlighting the urban heat burden and inland intensification of warm extremes.

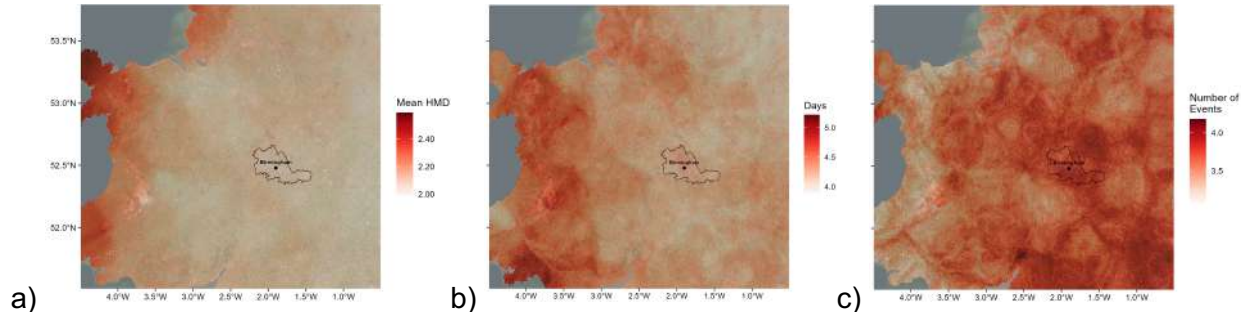


Figure 18: Spatial distribution of heatwave metrics for a wide area surrounding the Birmingham CSA for climate context, showing (a) mean annual cumulative intensity ($^{\circ}\text{C}$), (b) mean annual duration (days), and (c) mean annual occurrence of heatwave events for the years 1990–2022.

The temporal evolution of mean heatwave cumulative intensity over the wide area (Figure 19a) shows substantial seasonal and interannual variability, with values ranging between approximately 3°C and 8°C . In a few instances, this threshold is exceeded, particularly during spring and summer months. This pattern becomes more pronounced in the mean maximum intensity (Figure 19b), which frequently surpasses 8°C , reflecting the intensification of peak events in recent years. During the earlier part of the study period, many seasons exhibit no detected heatwave events, reflected in zero values for both intensity and duration. However, this becomes increasingly rare in recent years, contributing to a positive trend across both intensity metrics. The mean heatwave duration (Figure 19c) generally spans three to six days, though

numerous zero-event seasons still occur. Several outliers, however, reach durations of up to 11 days, with the longest-lasting event observed in summer 1997. Other notably prolonged events occur in summers 1991 and 2018, underscoring the persistence of extreme heat during those periods. The mean annual number of heatwave events (Figure 19d) shows a slight increase, indicating to the growing prevalence of multi-event seasons towards the end of the study period. Most seasons exhibit one event, with two-event seasons becoming more common in later years. Three and four-event seasons appear occasionally as outliers, primarily during spring and summer, with only a single case in winter, highlighting the seasonal concentration of heatwave events in the greater area of the CSA.

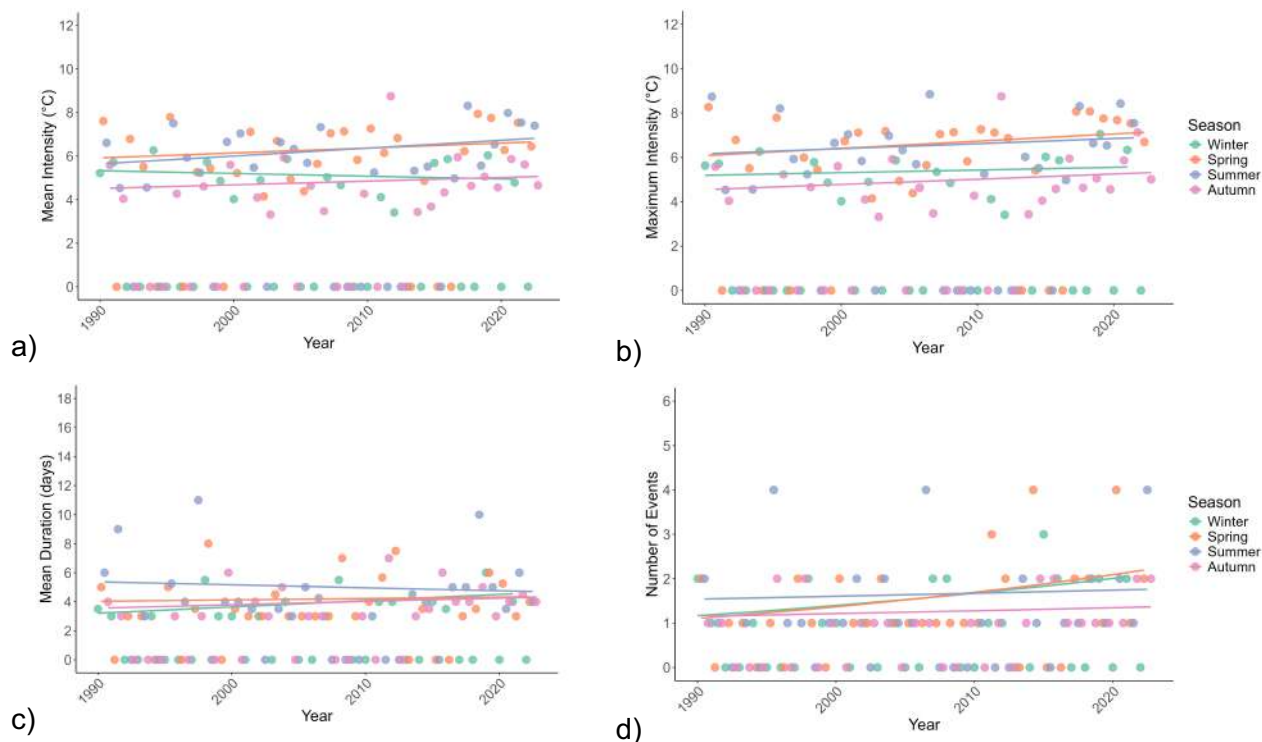


Figure 19. Temporal distribution of heatwave metrics for the greater CSA Birmingham area, showing (a) mean cumulative intensity (°C), (b) maximum intensity (°C), (c) mean duration (days), and (d) mean occurrence of heatwave events for each season during the period 1990–2022. The trend for non-zero values for each season is estimated using linear regression, except for heatwave frequency, where a generalized linear model was applied.

A comparative analysis of the eight CARMINE CSAs reveals distinct spatial patterns and temporal evolutions of heatwave characteristics across Europe. The Birmingham CSA and surrounding inland areas show a consistently elevated mean heatwave occurrence metric for the period 1990–2022. Barcelona stands out among the urban cores for its high mean heatwave intensity, which coincides with prolonged event durations and a strong upward trend in both intensity and frequency. Bologna similarly exhibits a marked increase over time, with exceptionally long heatwaves such as the 22-day event in summer 2022 and the highest number of six events in spring 2007. Brasov, in contrast, shows a slight decline in average intensity, but continues to register some of the most extreme single events, including intensity peaks above 11 °C and prolonged durations. Athens experiences frequent and persistent heatwaves, particularly in recent

years, with increasing seasonal coverage and longer durations—some exceeding 14 days. In Leipzig, a clear upward trend is seen in both mean and maximum intensity, particularly toward the end of the study period, although the region's south-eastern half remains less affected overall. Prague displays relatively moderate but spatially widespread heatwave conditions, with increasing seasonal frequency and rising maximum intensities, especially in summer. Funen-Odense stands out as a coastal region dominated by storm surge hazards but still exhibits relevant heatwave activity, with inland areas showing higher intensity and frequency trends. Overall, Barcelona, Bologna, and Birmingham emerge as the most dynamically affected urban areas in terms of heatwave escalation, while Brasov and Athens face persistent or extreme conditions. These diverse trends underscore the importance of tailored, region-specific adaptation strategies that account for both current vulnerabilities and projected intensification of heat stress across multiple European climate zones.

3.7 Droughts

The maps presented in this section illustrate the spatial distribution of key drought characteristics, namely mean drought intensity, calculated over the period 1990–2022 for each grid point within the respective CSAs (Figure 20a, Figure 21a & Figure 22a). Seasonal maps can be found in Annex: **Error! Reference source not found.. Error! Reference source not found..** The temporal figures display the evolution of drought conditions, as spatial aggregates over the greater areas surrounding the CSAs, including the annual drought intensity (Figure 20b, Figure 21b & Figure 22b) and the annual number of dry months (Figure 20c, Figure 21c & Figure 22c), thereby providing insight into both the severity and temporal frequency of drought events across the CSAs concerned with drought events. These visualizations offer a comprehensive overview of spatial and temporal/seasonal drought variability, facilitating the identification of regions experiencing recurrent or intensifying water stress throughout the period 1990–2022.

3.7.1 CSA Barcelona

The mean drought intensity in the greater CSA Barcelona area (Figure 20a) reveals several isolated areas, primarily located in the periphery of the region, displaying elevated drought intensities, with SPEI-1 values reaching -1.7. These hotspots indicate more severe drought conditions. In contrast, the area directly surrounding the city of Barcelona itself exhibits less negative SPEI-1 values across the region, indicating relatively milder drought conditions during the period 1990–2022. The temporal evolution of mean annual drought intensity (Figure 20b) in Barcelona indicates an absence of drought conditions during the initial four years of the study period. However, from that point onward, droughts occur continuously in the area with only a couple of exceptions, and with SPEI-1 ranging between -1.0 and -1.5. Notable deviations occur in the years 1997, 2005, and 2016, which show most pronounced drought intensities. The number of drought months (Figure 20c) is therefore also zero in the first years and subsequently varies between around one and four months per year. A distinct outlier is observed in 2022, which recorded approximately seven drought months, therefore being an exceptionally dry year relative to the rest.

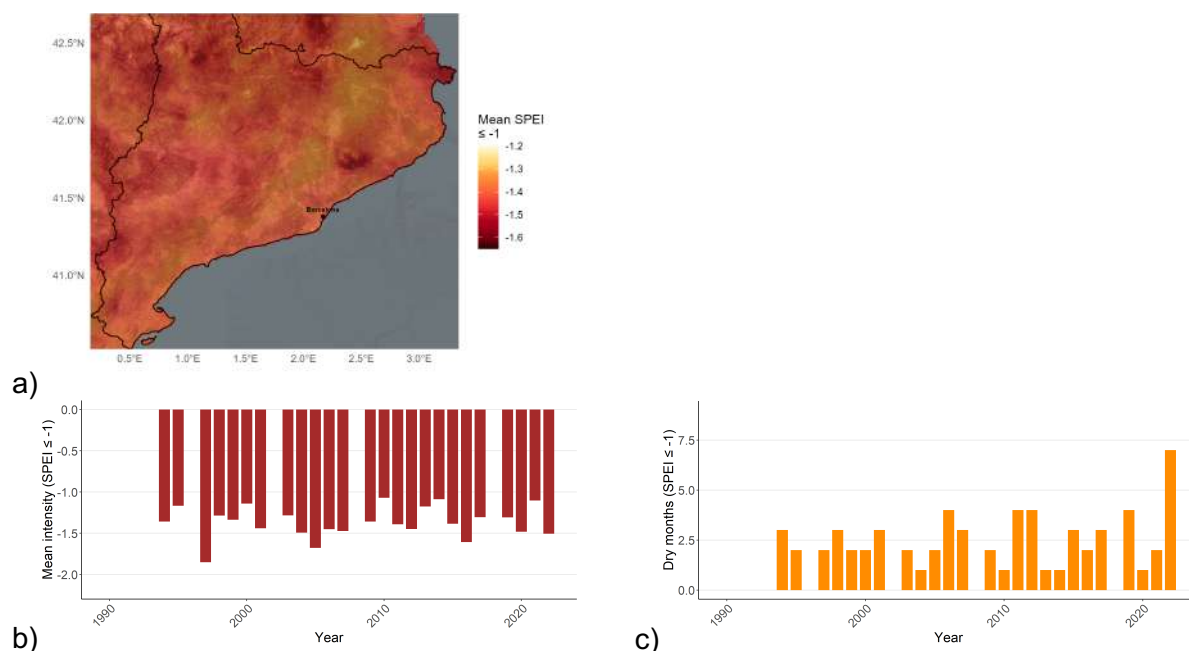


Figure 20: Drought characteristics for the greater CSA Barcelona area based on SPEI-1 ≤ -1 (reference period 1992–2022), showing (a) mean drought intensity, (b) annual drought intensity and (c) number of dry months per year, during 1990–2022.

3.7.2 CSA Brasov

The mean drought intensity in the greater CSA Brasov area during 1990–2022 (Figure 21a) reveals a pattern of more intense drought conditions in the northern part of the study area, in which the city of Brasov is also located. Additional regions with elevated drought intensity include parts of the Fagaras Mountains, the areas east of Bucegi National Park, and the northeastern portion of the area. The mean annual drought intensity (Figure 21b) indicates an absence of drought conditions during the years 1994–1998, as well as in 2010 and 2021. Although interannual variability is evident, drought intensity typically fluctuated between -1.0 and -1.5 SPEI-1, with particularly severe conditions in 2004 and 2011, when values dropped below -1.5. The number of drought months per year (Figure 21c) shows that Brasov experienced at least one to three dry months in most years, apart from those without any drought conditions. Notable peaks of five or more dry months occurred in 2000, 2007, 2012, and 2022, with the year 2000 emerging as the most extreme case, recording up to seven drought months.

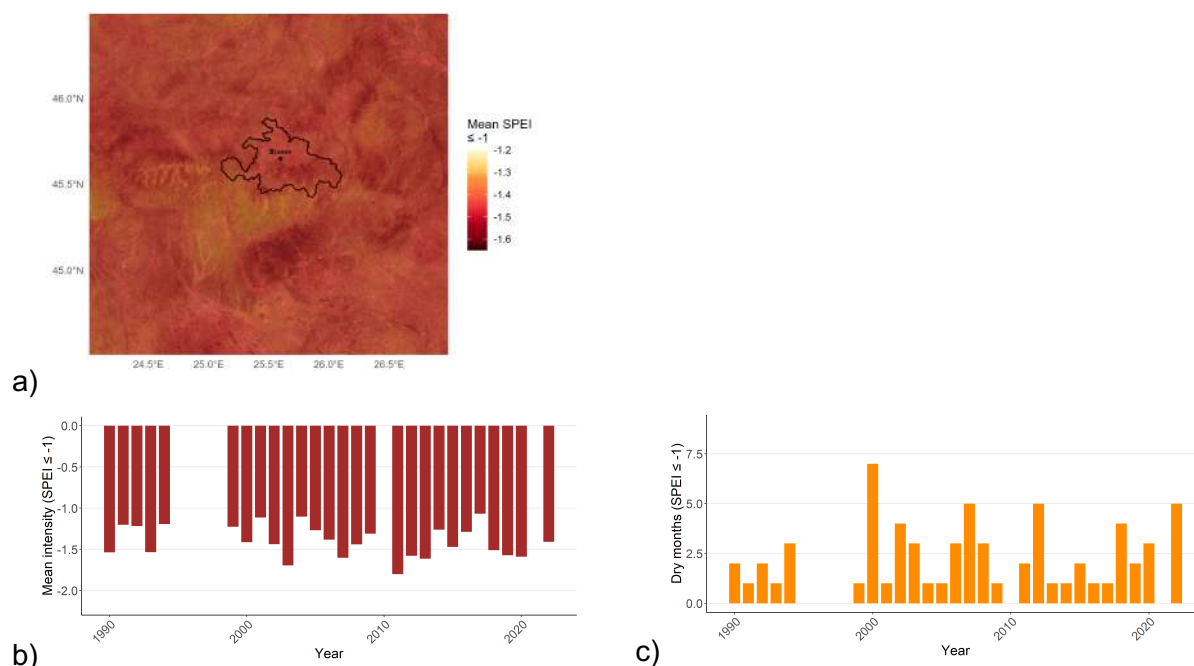


Figure 21: Drought characteristics for the greater CSA Brasov area based on the SPEI-1 ≤ -1 (reference period 1992–2022), showing (a) mean drought intensity, (b) mean annual drought intensity and (c) number of dry months per year, during 1990–2022.

3.7.3 CSA Prague

The mean drought intensity in the greater CSA Prague area (Figure 22a) reveals several areas displaying elevated drought intensities, with SPEI-1 values exceeding -1.6. These hotspots indicate more severe drought conditions and are visible especially to the northeast and southwest of Prague. However, elevated values are also present within the urban area of Prague, where they are especially visible in the south-western region. The temporal evolution of mean annual drought intensity (Figure 22b) in Prague indicates an absence of drought conditions during four years of the study period, namely 1999, 2001, 2016 and 2017. Otherwise, droughts occur continuously in the area with SPEI-1 ranging between -1.0 and -1.9. The most pronounced drought intensities occur in the middle of the period, with 2007 showing the most severe drought conditions. The number of drought months (Figure 22c) is therefore also zero in the corresponding four years and otherwise varies between around one and four months per year. Distinct outliers are observed in 1990 and 2018, which recorded approximately six drought months, therefore being exceptionally dry years relative to the rest.

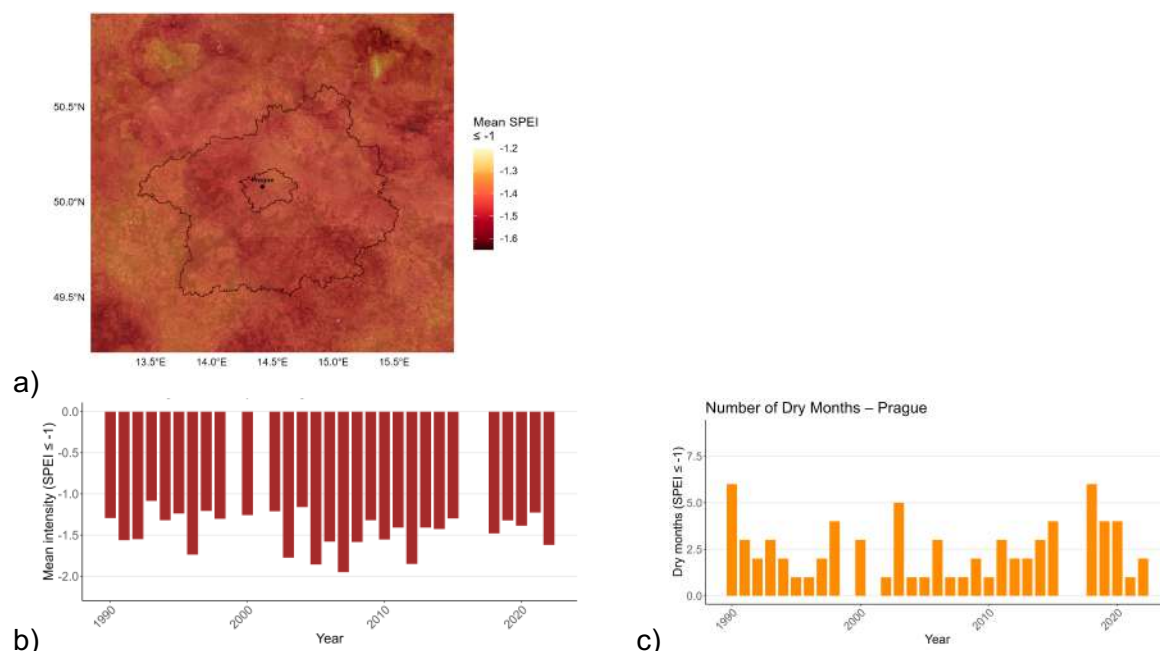


Figure 22: Drought characteristics for the greater CSA Prague area based on the $SPEI-1 \leq -1$ (reference period 1992–2022), showing (a) mean drought intensity, (b) mean annual drought intensity and (c) number of dry months per year, during 1990–2022.

The greater CSA Barcelona, CSA Brasov, and CSA Prague show distinct drought characteristics. In Barcelona, droughts are spatially fragmented, with peripheral hotspots and milder conditions near the urban core. Brasov, by contrast, shows centrally concentrated drought severity, with the city itself in one of the most affected zones. Prague shows hotspots of elevated drought conditions spread throughout the greater CSA, with areas northeast and northwest of the city experiencing the most severe conditions. Both CSAs Barcelona and Brasov experienced drought-free years early in the study period, but Brasov has more frequent and severe events. In Prague, there are fewer drought-free years, which also started to take place later in the study period. SPEI-1 values in all areas typically range between -1.0 and -1.5, though Prague records more extreme years, followed by Brasov. Brasov and Prague also show a higher number of drought months annually, while Barcelona's drought periods are fewer and more irregular, except in 2022, which was exceptionally dry.

3.8 Floods, Extreme Precipitation, Wet Events

The maps presented in this section illustrate the mean wetness intensity during 1990–2022 (Annex 9.2 Seasonal Wetness Maps) for each grid point within the respective CSAs (Figure 23a - Figure 26a). These maps provide a spatial overview of areas consistently affected by wetter-than-average conditions across the greater CSA areas. In addition, the temporal figures display spatial aggregates over the whole area, the annual evolution of wetness conditions, including mean annual intensity of wet months (Figure 23b - Figure 26b), as well as the annual number of wet months per year (Figure 23c - Figure 26c), thereby allowing assessment of both the intensity and frequency of wet extremes across time.

3.8.1 CSA Leipzig

The mean wetness intensity in the greater CSA Leipzig area during 1990–2022 (Figure 23a) exhibits rather irregular patterns across the region. Moderate to very wet conditions are primarily concentrated in the western parts of the CSA, where SPEI-1 values reach up to approximately +1.7, while the northeastern areas display more uniformly moderate wetness conditions. The temporal evolution of wet conditions (Figure 23b) reveals that most years during the study period are characterized by mean SPEI-1 values between 1 and 2, indicating moderate to high wetness conditions. A discernible decrease in wetness intensity is observed in the last decade. Correspondingly, the number of wet months per year (Figure 23c) reflects this decline, with most recent years registering only one wet month. Earlier in the record, however, higher frequencies of wet months are more common, with years such as 2002 and 2010 standing out for experiencing five and six wet months, respectively.

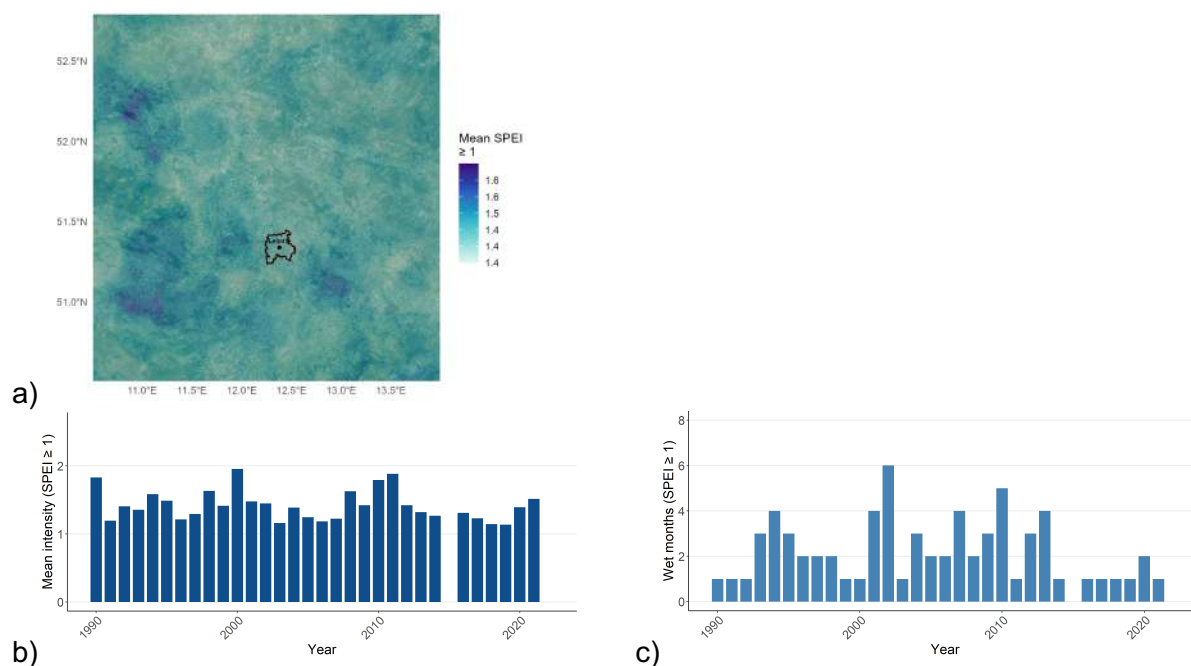


Figure 23: Wetness characteristics for the greater CSA Leipzig area based on the $SPEI-1 \geq 1$ (reference period 1992–2022), showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.8.2 CSA Funen-Odense

The mean wetness intensity in the greater CSA Funen-Odense area during 1990–2022 (Figure 24a) reveals heterogeneous values across the region, with the highest values in the southern coastal area and elevated values in the west and some northern parts. Except for the years 2000, 2005, 2013, and 2017, both the average wetness intensity (Figure 24b) and the annual number of wet months (Figure 24c) display irregular variability without pronounced extremes. The mean wetness intensity (Figure 24b) approaches a SPEI-1 value of +2, indicating very wet conditions, on several occasions, while the number of wet months per year reaches a maximum of four in five separate years, indicating sporadic but occasionally more persistent and very wet conditions.

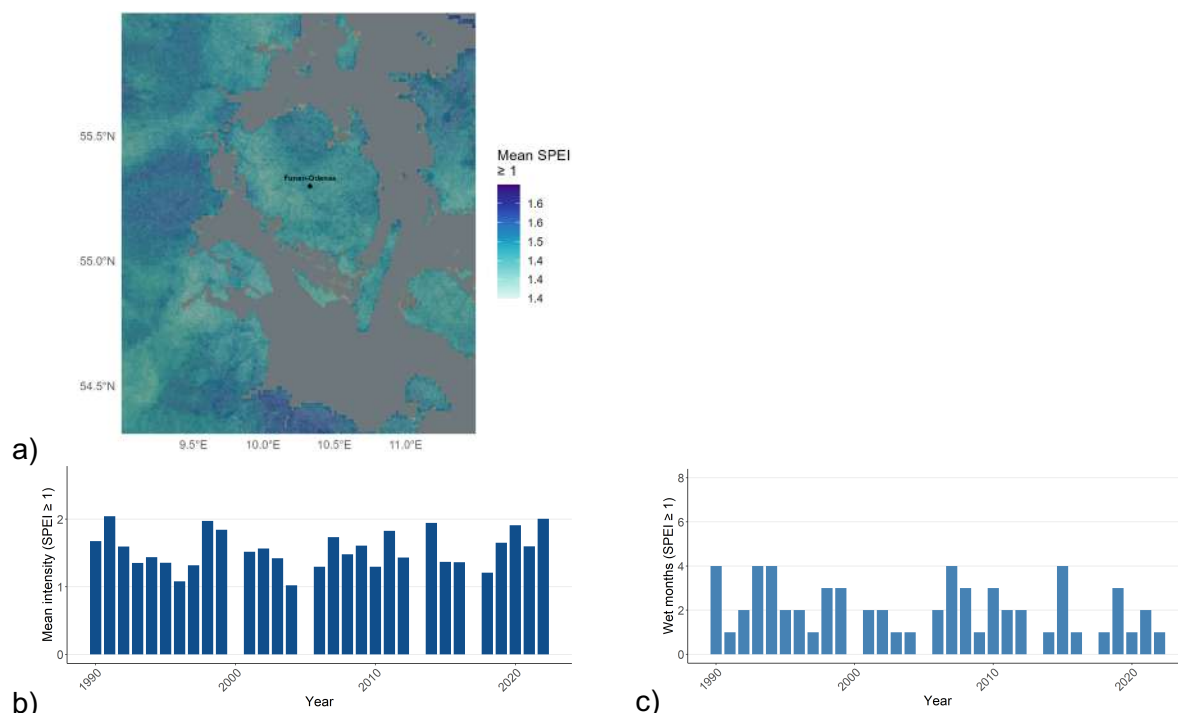


Figure 24: Wetness characteristics for the greater CSA Funen-Odense area based on the SPEI-1 ≥ 1 (reference period 1992–2022), showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.8.3 CSA Brasov

The mean wetness intensity in the greater CSA Brasov area during 1990–2022 (Figure 25a) shows a heterogeneous pattern, with the most pronounced wet conditions occurring in the western parts of the region, particularly around parts of the Fagaras Mountains. Comparable areas of elevated wetness intensity are also found north of the city, as well as in the south-eastern area. In contrast, the area surrounding Brasov exhibits less intense wet conditions. The mean annual wetness intensity of wet months (Figure 25b) reveals that with the exception of 1994, 2000, and 2011, most years display moderate interannual fluctuations. The year 1991 stands out as a particularly wet year, with a mean SPEI-1 exceeding +2. Regarding the annual number of wet months (Figure 25c), more frequent wet conditions are observed in the second half of the study period, with 2010 and 2018 reaching the highest count of five wet months. Most years, however, register between one and three wet months.

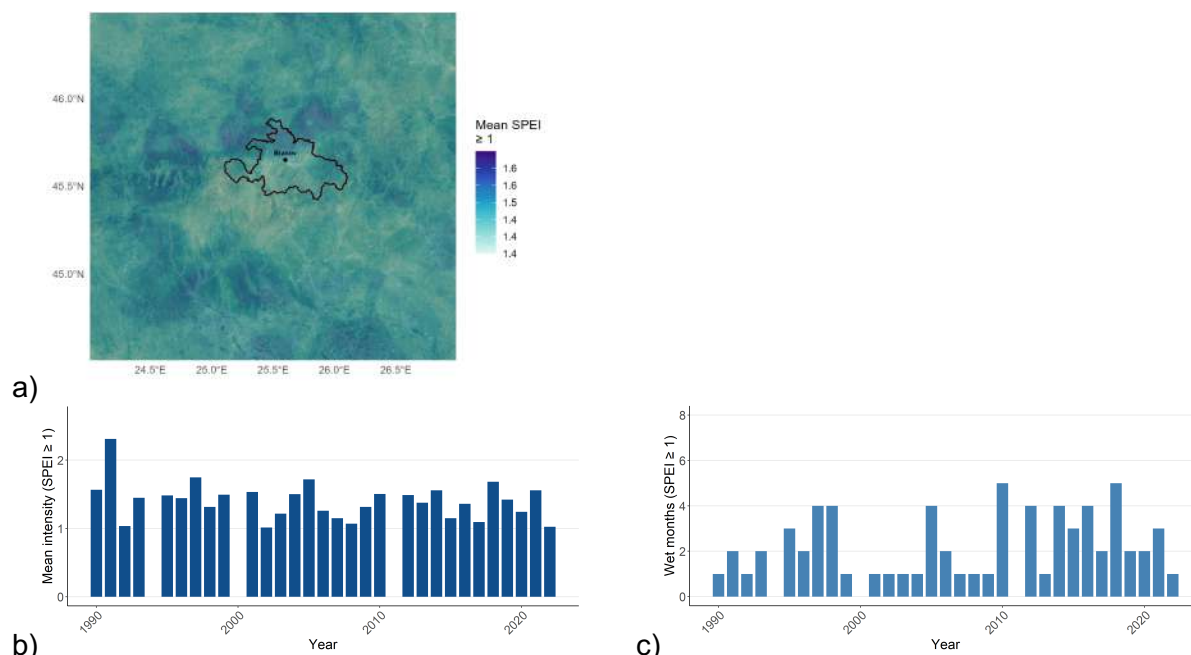
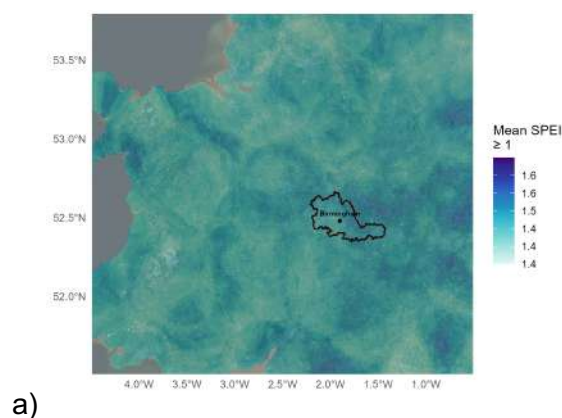


Figure 25: Wetness characteristics for the greater CSA Brasov area based on the SPEI-1 ≥ 1 (reference period 1992–2022), showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

3.8.4 CSA Birmingham

The mean wetness intensity in the greater CSA Birmingham area during 1990–2022 (Figure 26a) indicates that the south-western areas experience more pronounced humid conditions than the coastal regions. The mean annual wetness intensity (Figure 26b) shows several years, particularly in the first half of the period, without an occurrence of wet conditions. Furthermore, the highest wetness intensities across the wider area are observed in more recent years, with 2009 and 2021 approaching a mean SPEI-1 value of +2 during a sequence of very wet to extremely wet years. Regarding the number of very wet months per year (Figure 26c), 2012 and 2019 stand out with five months each, while the early part of the study period predominantly features years with 0 to 2 very wet months. A general increase in very wet months is observed in the second half of the study period for the whole area.



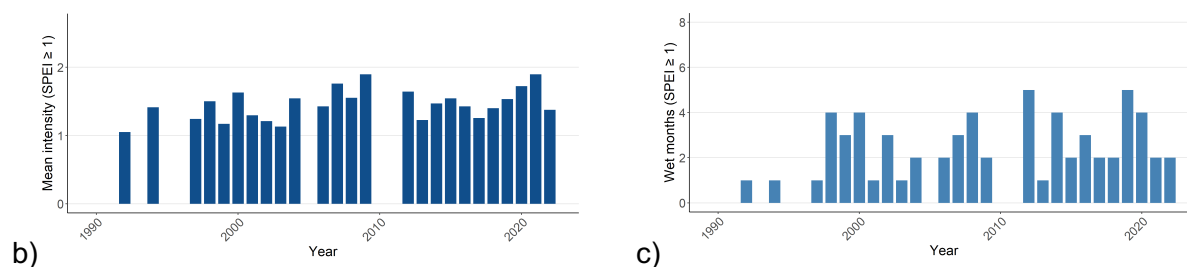


Figure 26: Wetness characteristics for the greater CSA Birmingham area based on the SPEI-1 ≥ 1 (reference period 1992–2022), showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

A comparative analysis of flood-related wetness conditions across the four CSAs reveals clear spatial and temporal differences. Leipzig exhibits irregular patterns of wetness intensities and the highest number of wet months, with consistent wet years such as 2002 and 2010. Birmingham shows a marked temporal shift, with limited wetness in the early period and stronger intensities and more wet months in recent years, particularly 2009 and 2021. Brasov shows localised wetness, particularly in the western and mountainous regions, with a low increase in wet months in the latter half of the study period. In contrast, Funen-Odense displays generally elevated wetness levels with greater coverage and several extreme years. Overall, Birmingham and Funen-Odense present a higher flood-related risk due to greater or increasing wetness intensity and frequency, while Brasov and exhibits more moderate and spatially variable conditions.

3.9 Compound Events, Combined Stress of Hot, Dry and Wet Events

Extreme events such as heatwaves, droughts, and heavy rainfall are linked to major socio-economic impacts (Zampieri et al., 2017; Zscheischler and Fischer, 2020; Hao et al., 2022; Xoplaki et al., 2025). These impacts can be significantly amplified when events co-occur in space or time, as many systems, especially in metropolitan areas, can withstand single extremes but not multiple, interacting stressors (Leonard et al., 2014; Hao et al., 2018; Zscheischler et al., 2018; Zscheischler and Fischer, 2020; Zhang et al., 2021; Hao et al., 2022). Concurrent extremes often involve multiple variables or events whose impacts are compounded (Toreti et al., 2019). In urban settings, this includes bivariate anomalies, such as warm and dry conditions, which may not be extreme alone but jointly pose major risks to infrastructure and public health (Mahony and Cannon, 2018). Such compound events are increasingly recognized as key drivers of societal and environmental risk (Zscheischler et al., 2018). In cities, where interdependent systems magnify exposure, univariate risk assessments may underestimate real-world impacts and return periods (Raymond et al., 2020; Wahl et al., 2015; Zscheischler and Seneviratne, 2017). Understanding these multivariate dynamics is therefore essential for effective urban risk management. Among such events are dry and hot summers with multiple recent examples e.g., the summer 2018. A comprehensive overview of all extreme and compound events that occurred across Europe in the calendar year 2018 is provided in Xoplaki et al. (2025).

3.9.1 *Dry and Hot Summers*

Compound dry-hot events in summer, characterized by the simultaneous or sequential occurrence of drought and extreme heat, pose significant and cascading threats across multiple sectors. In agriculture, they lead to reduced soil moisture and elevated evapotranspiration, causing crop failures, livestock stress, and heightened food insecurity. Water availability declines as reservoirs and groundwater are depleted, disrupting drinking water supplies, irrigation systems, and hydropower production. Ecosystems suffer from increased wildfire risk, forest dieback, and biodiversity loss, while human health is compromised by heat-related illnesses, air pollution from fires, and mental health impacts. These events also place economic pressure on energy systems, damage infrastructure, and reduce labour productivity, resulting in major financial losses. Additionally, dry-hot conditions contribute to climate feedbacks, such as enhanced carbon release from wildfires and increased heat absorption by desiccated soils, thereby intensifying global warming. Addressing these risks requires targeted adaptation measures, including resilient infrastructure, improved water governance, and integrated climate strategies. As climate change accelerates the frequency and severity of these compound events, their far-reaching impacts call for immediate and coordinated global responses.

3.9.2 *Combined Stress Index*

The calculation of CSI for the greater areas of the CARMINE CSAs provides information on the occurrence, persistence and frequency of joint events of heat, drought or wet conditions. The annual mean values of events that exceed 1 standard deviation of the reference period 1992–2022, denote the presence of extreme occurrences of such combinations of events. It should be noted once again that $\text{SPEI-1} \leq -1$ implies the occurrence of drought (and not only dry conditions), $\text{SPEI-1} \geq 1$ is related with very wet events, while HMD values provide information on the daily intensity of a detected heatwave event. The construction of CSI allows for a detection of areas susceptible to combined stress of heat extremes and droughts or heat and wet extremes. To enable and facilitate the interpretation of the CSI maps and the identification of the “driving variable”, heat or water balance, correlation maps between the CSI and the corresponding indicators, HMD and SPEI-1, are also provided.

3.9.3 *CSA Prague*

The spatial distribution of extreme (≥ 1 standard deviation) CSI values in CSA Prague (Figure 27a) shows a broad area of very high values around the city, with distinct hotspots northwest of Prague. Additional areas with CSI values > 2.5 are found in the southwest and northeast of the greater region. Overall, the most frequent compound events during 1990–2022 are heatwaves and droughts, as indicated by positive correlations with HMD (Figure 27b) and negative correlations with drought index SPEI-1 (Figure 27c), affecting both the core and surrounding areas of CSA Prague.

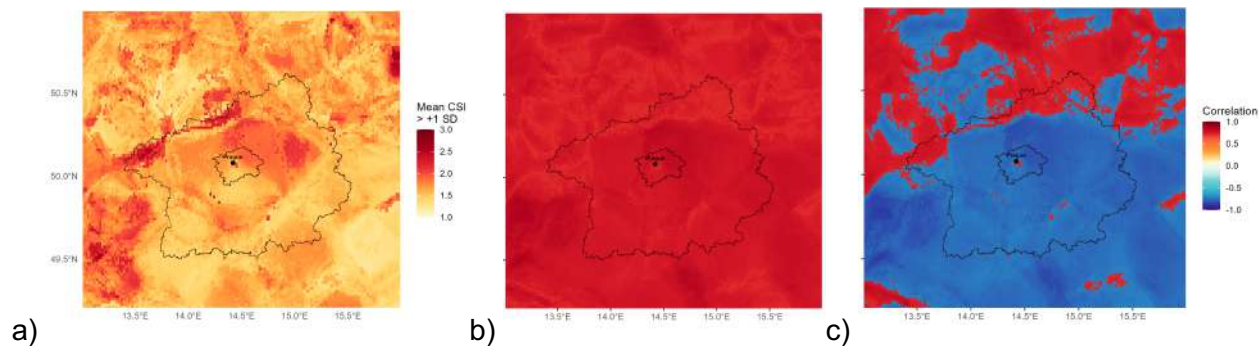


Figure 27: Combined impact of annual heat and hydrological extreme events in the greater CSA Prague area during 1990–2022; (a) spatial distribution of extreme (≥ 1 standard deviation) annual mean CSI, (b) correlation between CSI and HMD, (c) correlation between CSI and SPEI-1.

3.9.4 CSA Leipzig

In the greater CSA Leipzig area, the spatial distribution of extreme CSI values (Figure 28a) forms a continuous north-south band of elevated values that intersects the city and extends to the southern edge of the region. The highest CSI values (> 3) are observed south of Leipzig in a nature reserve. Figure 28b shows strong positive correlations between CSI and HMD (heatwave metric), while Figure 28c shows positive correlations with SPEI-1, indicating that hot and wet events are the dominant drivers. In contrast, areas with lower CSI values are more affected by hot and dry events.

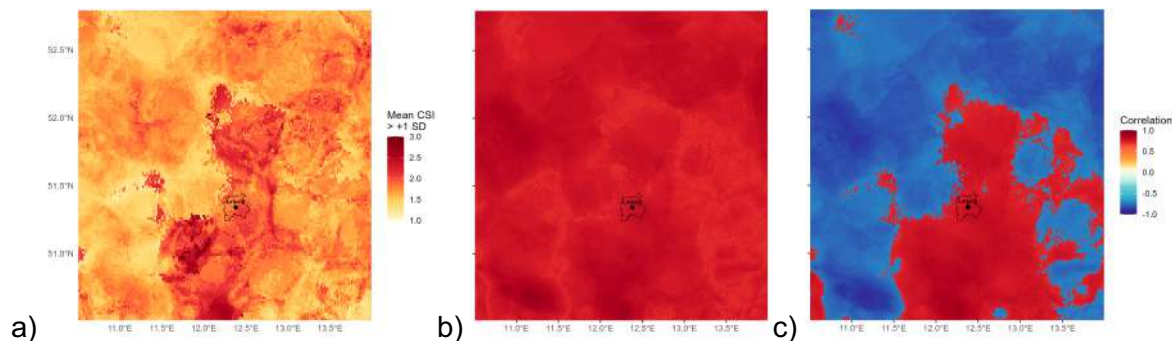


Figure 28: Combined impact of annual heat and hydrological extreme events in the greater CSA Leipzig area during 1990–2022; (a) spatial distribution of extreme (≥ 1 standard deviation) annual mean CSI, (b) correlation between CSI and HMD, (c) correlation between CSI and SPEI-1.

3.9.5 CSA Funen-Odense

Figure 29a shows that extreme CSI values (≥ 1 standard deviation) in the greater CSA Funen–Odense area peak in the northern part of the region and southwestern mainland areas, while lower values occur in the northwest and along the southern and western coasts of Funen Island. The influence of compound hot and dry events is supported by strong correlations with HMD (Figure 29b) and negative correlations with SPEI-1 (Figure 29c).

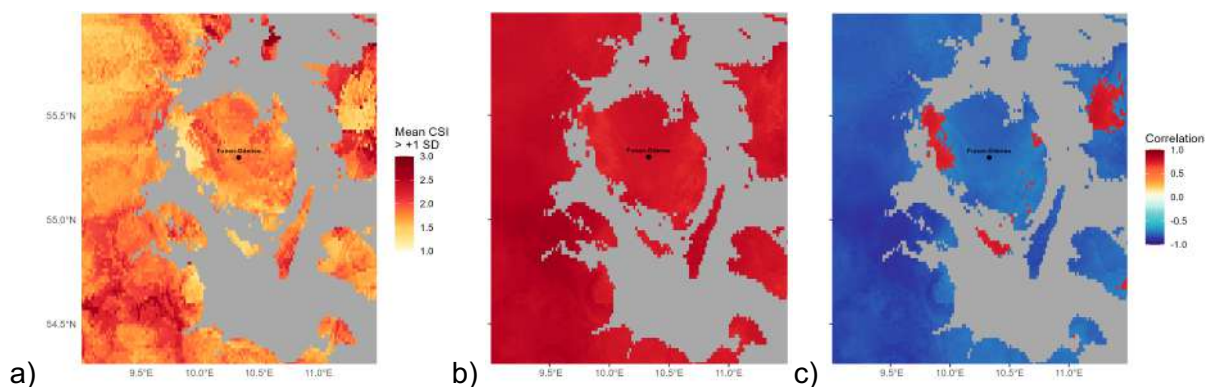


Figure 29: Combined impact of annual heat and hydrological extreme events in the greater CSA Funen-Odense area during 1990–2022; (a) spatial distribution of extreme (≥ 1 standard deviation) annual mean CSI, (b) correlation between CSI and HMD, (c) correlation between CSI and SPEI-1.

3.9.6 CSA Athens

The greater CSA Athens area exhibits widespread and extreme CSI values (≥ 3), particularly across the metropolitan area and extending into central Greece, with additional hotspots in the Peloponnese and inland areas (Figure 30a). Figure 30b and Figure 30c confirm that the region is predominantly affected by compound hot and dry events. However, smaller pockets of hot and wet events are visible over several Aegean islands and coastal locations.

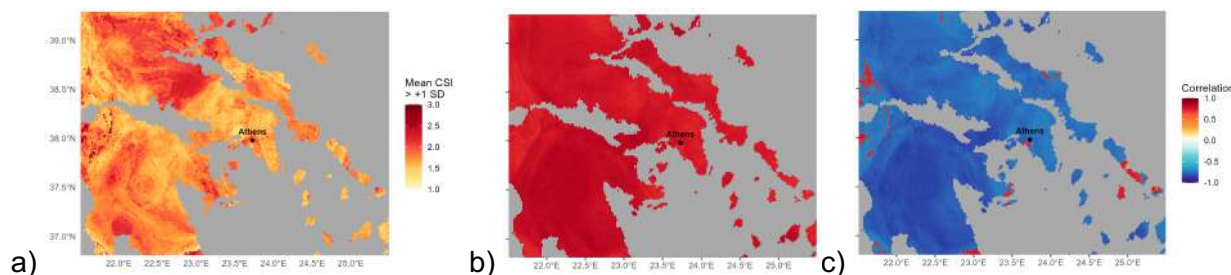


Figure 30: Combined impact of annual heat and hydrological extreme events in the greater CSA Athens area during 1990–2022; (a) spatial distribution of extreme (≥ 1 standard deviation) annual mean CSI, (b) correlation between CSI and HMD, (c) correlation between CSI and SPEI-1.

3.9.7 CSA Barcelona

The spatial pattern of extreme CSI values (Figure 31a) in the greater CSA Barcelona area is heterogeneous, with hotspots around the city, particularly to the southwest and northwest. These areas are affected by both hot and wet events (positive correlations in Figure 31c) and hot and dry events (negative correlations in Figure 31c). While inland areas show scattered, isolated extremes, the coastal zone is more consistently impacted by compound hot and wet events. The overall distribution of CSI values is patchy and localized.

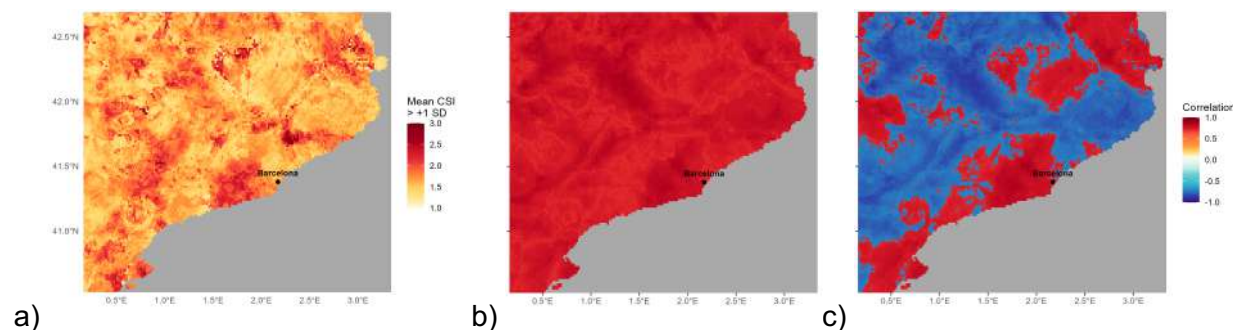


Figure 31: Combined impact of annual heat and hydrological extreme events in the greater CSA Barcelona area during 1990–2022; (a) spatial distribution of extreme (≥ 1 standard deviation) annual mean CSI, (b) correlation between CSI and HMD, (c) correlation between CSI and SPEI-1.

3.9.8 CSA Bologna

In the greater CSA Bologna area, the spatial distribution of extreme CSI values (Figure 32a) reveals several high-impact zones, especially in the west and around the metropolitan area. Figure 32b and Figure 32c indicate that the region is primarily affected by compound heatwaves and droughts, particularly in the northwest and south of Bologna. However, Bologna itself is more influenced by hot and wet events (positive CSI–SPEI-1 correlation).

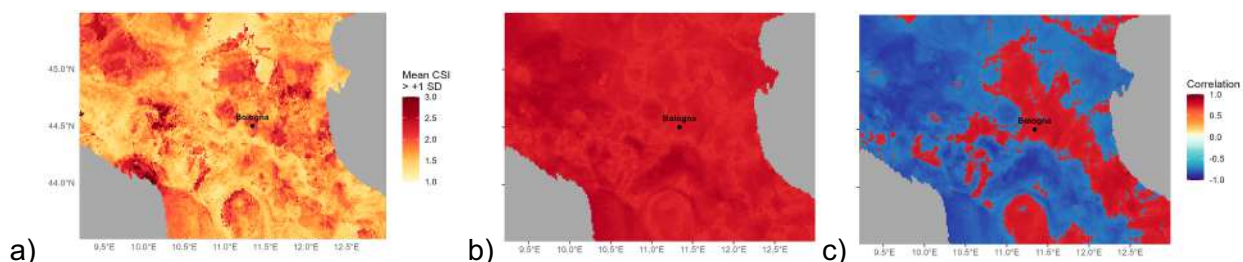


Figure 32: Combined impact of annual heat and hydrological extreme events in the greater CSA Bologna area during 1990–2022; (a) spatial distribution of extreme (≥ 1 standard deviation) annual mean CSI, (b) correlation between CSI and HMD, (c) correlation between CSI and SPEI-1.

3.9.9 CSA Brasov

The greater CSA Brasov area shows pronounced extreme CSI values over the metropolitan area and to the east (Figure 33a), with additional elevated patches near the urban core and scattered across the region. Compound hot and dry events dominate most of the area, as seen in Figure 33b (positive HMD correlations) and Figure 33c (negative SPEI-1 correlations).

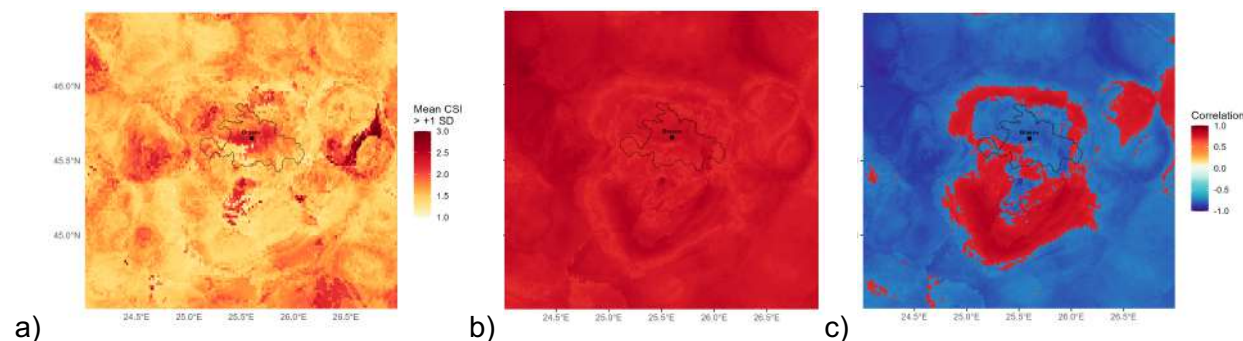


Figure 33: Combined impact of annual heat and hydrological extreme events in the greater CSA Brasov area during 1990–2022; (a) spatial distribution of extreme (≥ 1 standard deviation) annual mean CSI, (b) correlation between CSI and HMD, (c) correlation between CSI and SPEI-1.

3.9.10 CSA Birmingham

Figure 34a shows a continuous band of extreme CSI values in the wide area surrounding the Birmingham CSA, stretching from the western edge of the region through the CSA to the north-northeast. Most of the region displays elevated values, especially over the Birmingham metropolitan area, the strong impact of compound events is very high and over 2 standard deviations. Figure 34b and Figure 34c indicate that compound heatwaves (positive correlations) and droughts (negative correlations) are the dominant events affecting the region.

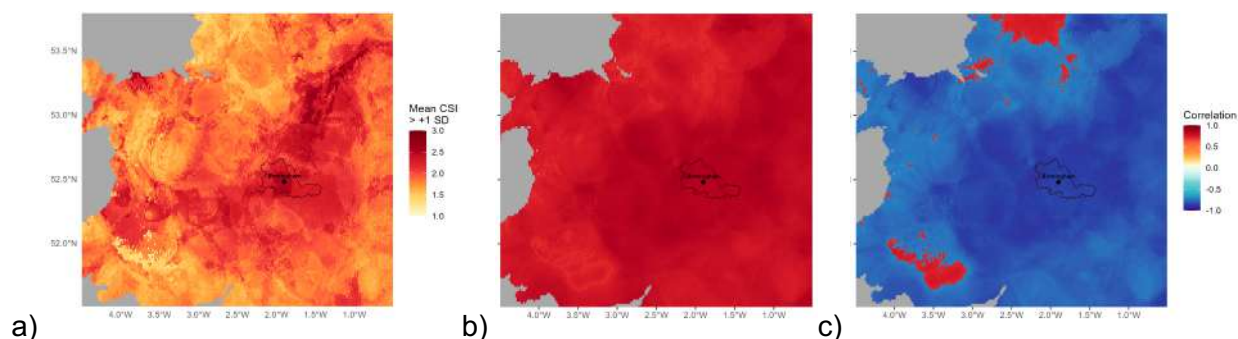


Figure 34: Combined impact of annual heat and hydrological extreme events in the greater CSA Birmingham area during 1990–2022; (a) spatial distribution of extreme (≥ 1 standard deviation) annual mean CSI, (b) correlation between CSI and HMD, (c) correlation between CSI and SPEI-1.

3.10 Hotspot Areas in CSAs

The following section presents plots illustrating the spatial distribution of heatwave, drought, and wet event probabilities across all CSAs. Each pixel's colour represents the annual likelihood of a climate extreme occurring at that location, scaled from 0 to 1. The classes used are: 0-0.20 very low probability, 0.21-0.40 low probability, 0.41-0.60 moderate probability, 0.61-0.80 high probability and 0.81-1 very high probability. As defined earlier, a heatwave is a period of at least three consecutive days during which the daily maximum temperature exceeds the 90th percentile of a defined reference period, here 1992–2022. Droughts are identified by a SPEI-1 ≤ -1 , while wet conditions correspond to SPEI-1 ≥ 1 .

3.10.1 CSA Prague

The probability plots of the greater CSA Prague area (Figure 35) reveal a high likelihood of all three hazards, heatwaves, droughts, and wet events, occurring across the area, including within the urban core of Prague. Heatwave probability is generally high across most of the CSA. The metropolitan area of Prague is characterized by moderate drought probability and a similar level of wet event occurrence, indicating overlapping risk zones even within the city.

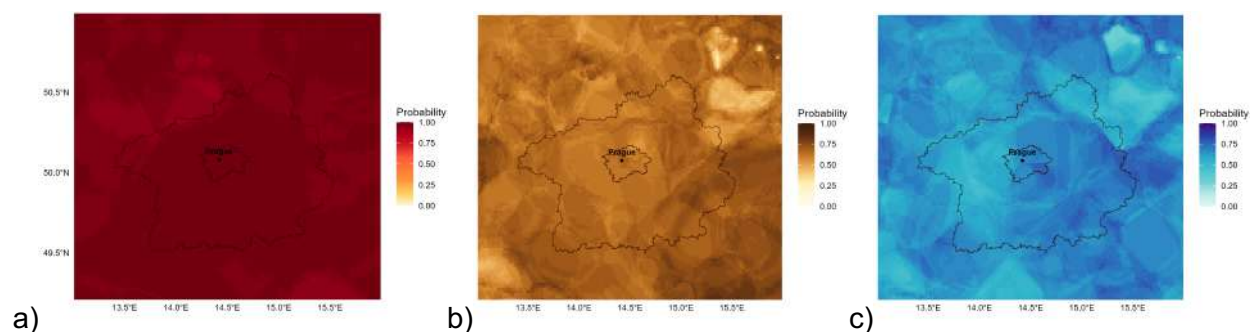


Figure 35: Greater CSA Prague area: Mean annual probability for the occurrence of a) heatwaves, b) droughts and c) wet events.

3.10.2 CSA Leipzig

The probability plots for the greater CSA Leipzig area (Figure 36) display a clear spatial division between the western and eastern areas of the region. The urban core of Leipzig experiences moderate probabilities for both heatwaves and drought, alongside localized wet event influence. The western portion is predominantly influenced by heat, with comparatively lower probabilities of droughts and wet events. In contrast, the eastern part of the CSA exhibits the influence of all three hazards, heat, drought, and wet events, over a broader spatial extent. This results in regions marked by multi-hazard exposure, particularly in the central and eastern areas.

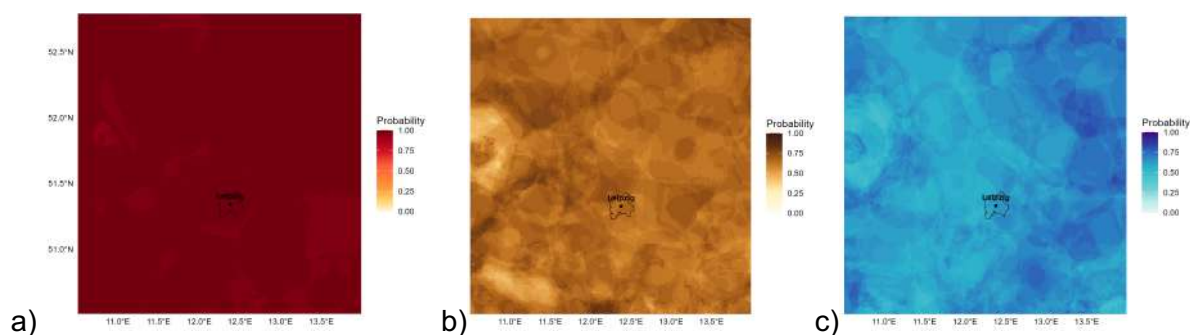


Figure 36: Greater CSA Leipzig area: Mean annual probability for the occurrence of a) heatwaves, b) droughts and c) wet events.

3.10.3 CSA Funen-Odense

The probability maps of the greater CSA Funen–Odense area (Figure 37) indicate that the island of Funen is largely affected by heatwaves, with parts of the area also showing moderate drought probabilities. The northeastern section of the CSA reveals a stronger drought signal, while the western regions exhibit overlapping probabilities for all three hazard types. Overall, the urban core of Odense is marked by a combination of heat and moderate drought probabilities, reflecting a compound hazard potential.

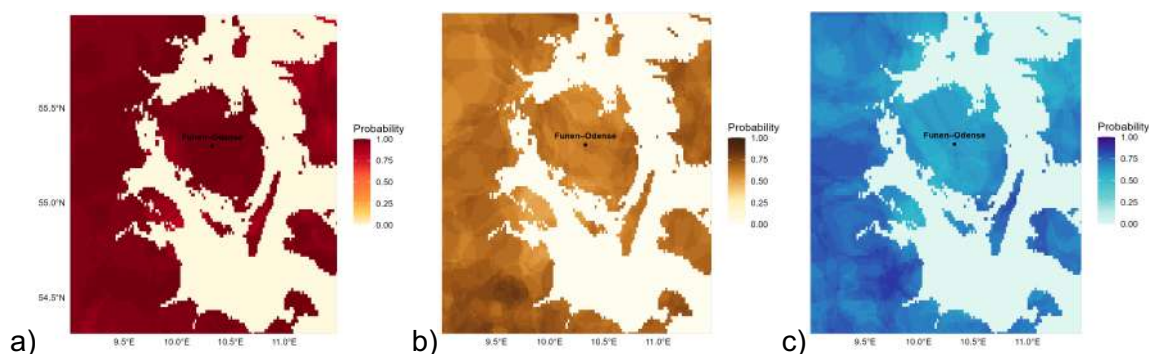


Figure 37: Greater CSA Funen-Odense area: Mean annual probability for the occurrence of a) heatwaves, b) droughts and c) wet events.

3.10.4 CSA Athens

The probability plots of the greater CSA Athens area (Figure 38) underscore the dominance of heatwave occurrence across the region and the city of Athens. Drought probability is also relatively high, particularly in areas to the north and southwest of the metropolitan area, resulting in combined heat-drought exposure zones. Wet event probability is moderate in the Athens metropolitan area and decreases toward the coastal areas east of the city. This spatial configuration points to compound heat and drought risks in inland zones, while coastal areas are more likely to experience isolated heatwave events.

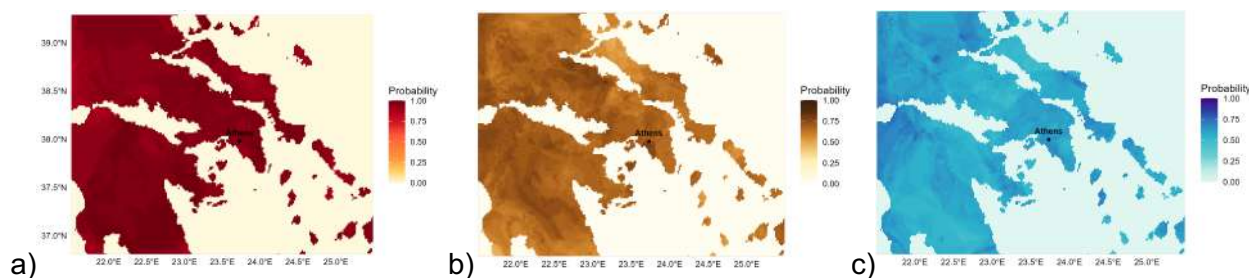


Figure 38: Greater CSA Athens area: Mean annual probability for the occurrence of a) heatwaves, b) droughts and c) wet events.

3.10.5 CSA Barcelona

The probability maps for the greater CSA Barcelona area (Figure 39) reveal the presence of all three climate hazards, heatwaves, droughts, and wet events, across the region. Within the urban core of Barcelona, there is a high likelihood of all three occurring, signifying a significant multi-hazard risk. Inland from the city, a broad corridor parallel to the coast is predominantly affected by heatwaves, while drought probabilities increase in the northeastern and southwestern parts of the greater area. Wet event probability is particularly high over the metropolitan area and the coastal fringes in the northeast and southwest, indicating spatial overlap with heat and drought hazards.

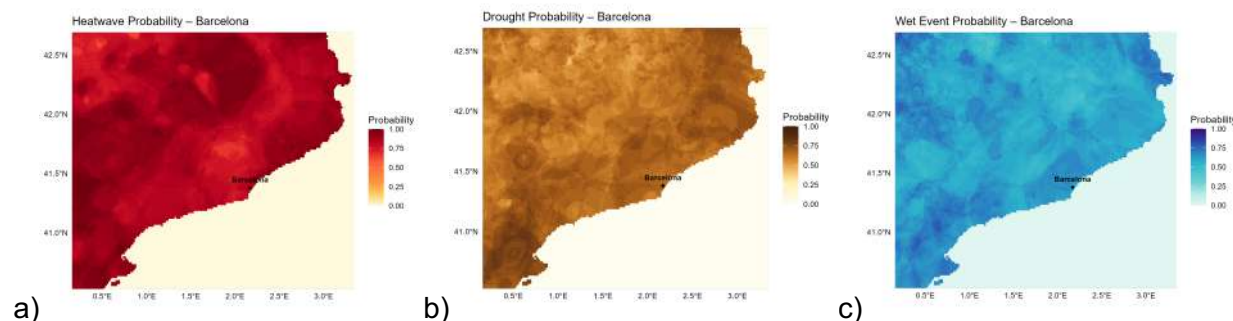


Figure 39: Greater CSA Barcelona area: Mean annual probability for the occurrence of a) heatwaves, b) droughts and c) wet events.

3.10.6 CSA Bologna

The probability maps for the greater CSA Bologna area (Figure 40) show the presence of all three hazards throughout the region. Hotspots for heatwave probability are especially evident to the north and south of the urban area, while the Bologna metropolitan area experiences high heatwave frequency and moderate drought risk. The northern and eastern sectors of the area display overlapping influence from heatwaves, droughts, and wet events. In the southern areas and coastal zones, wet event probability increases and heat influence decreases moderately. The western portion of the CSA is marked by moderate to high probabilities for drought and wet events, while heatwaves are notably less frequent. This spatial pattern reflects substantial heterogeneity in compound hazard exposure across the region.

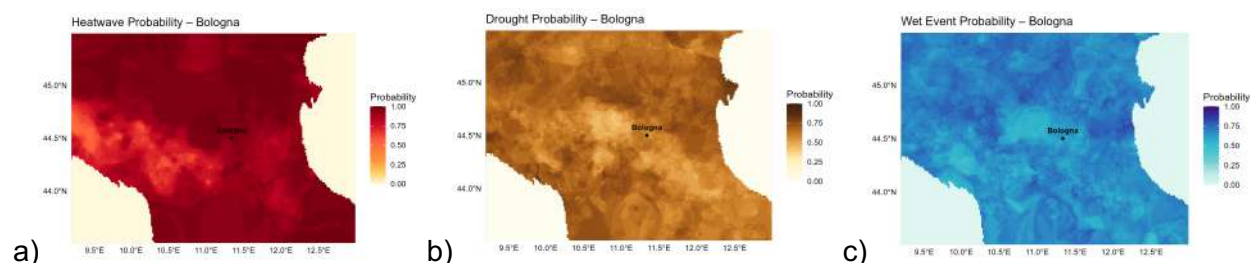


Figure 40: Greater CSA Bologna area: Mean annual probability for the occurrence of a) heatwaves, b) droughts and c) wet events.

3.10.7 CSA Brasov

The probability maps for the greater CSA Brasov area (Figure 41) highlight the surroundings of the city as a distinct hotspot for heatwave probability, combined with a moderate wet event influence. Further to the south and west, the probability of wet events becomes more pronounced, indicating specific sub-regions more vulnerable to humidity-related hazards. Heatwaves dominate much of the extended area, particularly in the central and northern areas. Drought influence is more notable in the western portions of the area, resulting in spatially differentiated risk profiles for Brasov and its surroundings.

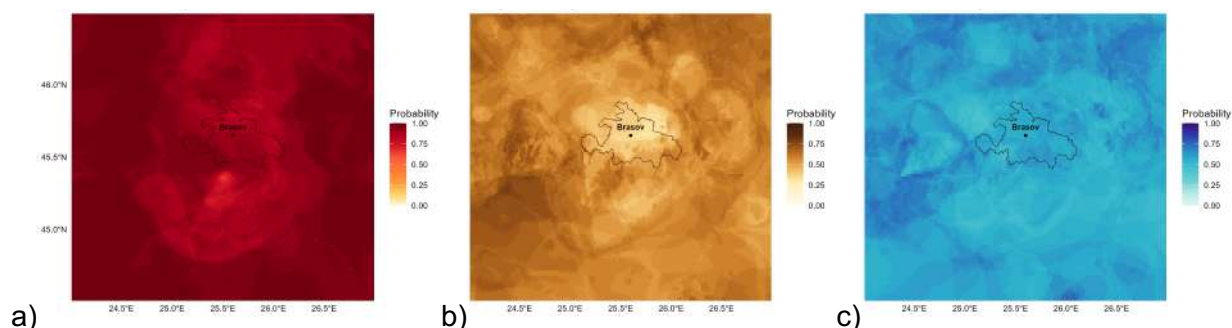


Figure 41: Greater CSA Brasov area: Mean annual probability for the occurrence of a) heatwaves, b) droughts and c) wet events.

3.10.8 CSA Birmingham

The probability plots for the wide area surrounding the Birmingham CSA (Figure 42) demonstrate an overall high likelihood of heatwave occurrence. The southwestern parts of the region show overlapping moderate to high probabilities for all three hazard types, heatwaves, droughts, and wet events. This complex hazard landscape continues inland, where heatwave probability remains high and is often accompanied by drought risk. Wet event probabilities are higher around Birmingham and southwest of the area, indicating localized potential for compound wet and heat or wet and drought conditions. The overall pattern underscores widespread hazard exposure across the CSA.

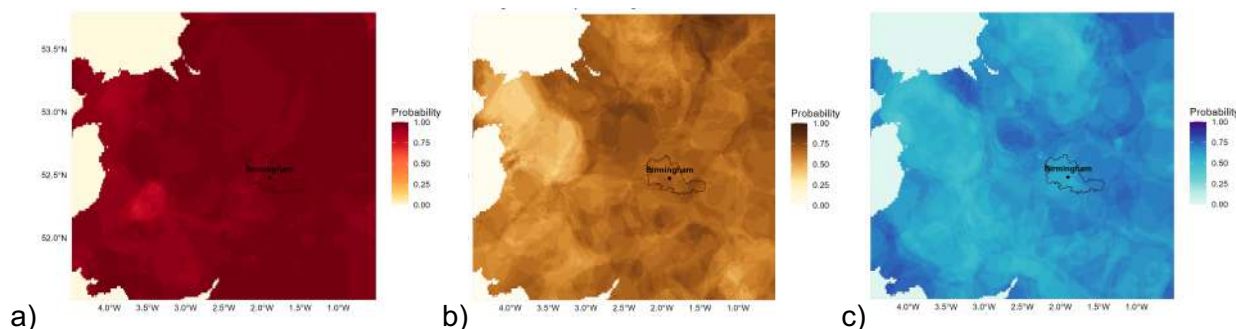


Figure 42: CSA Birmingham: Mean annual probability for the occurrence of a) heatwaves, b) droughts and c) wet events.

A comparative analysis of hazard probability across the eight CSAs shows that heatwaves are the most consistent threat, with moderate to high likelihoods across all regions. Urban cores such as Athens, Barcelona, Bologna, Brasov, Birmingham, and Prague are embedded within high-probability heatwave zones. Bologna and Brasov display particularly strong heatwave signals, often in combination with drought. Compound/overlapping heat-drought risks, based on annual probabilities, are frequent, especially in Athens, Barcelona, Bologna, and Leipzig, where overlapping hazards create areas of heightened exposure. Leipzig shows a unique spatial split, with western areas more heat-affected and eastern parts also showing wet hazard potential. CSA Barcelona and CSA Bologna exhibit the most complex multi-hazard profiles, with significant overlap of heat, drought, and wet event probabilities. CSA Prague and Funen–Odense display more moderate but widespread multi-hazard exposure. Brasov and Birmingham show localized

wet event influence, especially in southern areas. In sum, no CSA is hazard-free, and urban centres are often at the intersection of multiple threats, underscoring the importance of tailored, region-specific risk management approaches.

4. Disaster Risk Indices

4.1 The DRS Indices

Table 2 presents a selection of recognized DRS indices which enable a more comprehensive picture of disaster risk, by taking social, economic and institutional factors into account. In addition, the United Nations Economic Commission for Europe published “The Set of Core Disaster-Risk-Related Indicators” in 2025, which provides a harmonized framework of 53 key indicators designed to support countries in systematically assessing and monitoring disaster risk across sectors and hazard types. The work presents also an additional set of complementary indicators to capture more detailed, emerging, or context-specific aspects of disaster risk that may not yet be covered (United Nations Economic Commission for Europe 2025).

A further set of DRS indicators from the Bureau of the Conference of European Statisticians (CES) Task Force on Measuring Hazardous Events and Disasters is provided in Annex 9.8. Disaster risk indicators.

Table 1: Disaster risk indices, temporal resolution, associated hazards, applicability and references

Index	Name	Description	Temporal resolution	Associated hazard(s)	Applicability	References
CRI	Climate Risk Index	Analyses climate-related extreme weather events' economic and human effects on countries and, thereby, measures the realised risks' consequences for countries.	Yearly	Extreme weather events, including hydrological, meteorological, and climatological events.	Aggregation and understanding of climate impacts across different regions and time periods; Country-level comparisons; Spotlighting nations that are most severely affected; Policy advice.	Schäfer et al. (2025)
DRI	Disaster Risk Index	Quantifies risks of death per country in large- and medium-scale disasters using past data and exposure modelling and enables the identification of several socio-economic and environmental variables that are correlated with risk to death.	Multi-year average	Earthquakes; Tropical Storms; Floods	Identification of hazard exposure and vulnerability; Mortality risk assessment; Country-level comparisons.	Ramli et al. (2020) UNDP (2004)

INFORM	INFORM Risk Index – Index for Risk Management	Measures disaster risk and crisis potential globally based on exposure, vulnerability, and coping capacity	Annual	Natural hazards; Conflicts	Development. Risk assessment and reduction; Monitoring; Supporting decisions about crisis prevention, preparedness and response.	Marin-Ferrer et al. (2017)
ND-GAIN Index	Notre Dame Global Adaptation Initiative's Country Index	Shows a country's current vulnerability (exposure, sensitivity and adaptive capacity) to climate disruptions and assesses a country's readiness to leverage private and public sector investment for adaptive actions.	Annual	Climate-related hazards	Supporting decisions regarding supply chains, capital projects, policy changes and community engagements.	Chen et al. (2023)
WIR	World Risk Index	Further development and extension of the DRI, by also taking social resilience, coping skills and adaptation strategies into account.	Annual	Earthquakes; Floods; Storms; Droughts	Identification of hazard exposure and vulnerability; Risk assessment; Policy advice; Climate resilience strategies; Monitoring of risk development; Country- and region-level comparisons.	Ramli et al. (2020)

5. Modelling Framework

5.1 CSA Prague

5.1.1 Inventory of Existing Climate Scenarios and Tools

The modelling framework for CSA Prague integrates high-resolution urban climate modelling, air quality simulation, and health impact assessment to address key challenges such as heat stress and air pollution in a growing metropolitan context. It supports the development of evidence-based adaptation strategies aimed at improving urban liveability, public health, and climate resilience under present and future climate scenarios. Climate models such as WRF, COSMO-CLM, and the PALM model system are used to simulate weather conditions and urban climate dynamics. WRF provides temperature, wind, humidity, and precipitation outputs based on ERA5 and NCEP reanalyses for both event-based and long-term projections. COSMO-CLM downscales daily reanalysis and climate model data to generate high-resolution simulations for historical and future scenarios. The PALM model system captures urban turbulence and resolves urban heat island effects through advanced urban canopy modelling. Based on these outputs, air quality models

estimate future changes in pollution levels. CAMS provides regional data on greenhouse gases and aerosols, while GRAL and ATEM offer urban-scale air quality modelling, simulating local dispersion patterns in complex built environments. The modelling framework also incorporates health and epidemiological tools to assess population-level impacts, including daily mobility and climate-related mortality under various exposure scenarios. The modelling process draws on a range of observational and reanalysis data sources, including meteorological station records, ERA5, ALADIN forecasts, and high-resolution regional datasets. Key indicators include thermal comfort metrics such as air temperature, UTCI, PMD, and PMV, as well as air quality indices like AQI, pollutant concentration maps, and smog severity levels. These indicators enable a comprehensive assessment of environmental and health-related risks to inform urban climate adaptation in Prague.

5.1.2 Gap Analysis

A gap analysis revealed several data limitations for CSA Prague. For urban microclimate simulations, additional street-level thermal observations are needed to enhance model calibration and validation. Air quality assessments would benefit from a broader empirical dataset to improve the robustness of cross-model comparisons. Furthermore, a deeper understanding of socio-environmental dynamics requires improved integration between health records and climate exposure data. Ensuring long-term data consistency will necessitate the harmonization of datasets spanning multiple decades. Lastly, the inclusion of crowdsourced weather data could significantly enhance spatial resolution and foster community engagement in local climate monitoring.

5.1.3 Gap-Need Mapping

Table 3: Gap need mapping including corresponding stakeholder need and priority action for CSA Prague

Gap	Corresponding Stakeholder Need	Priority Action
Lack of high-resolution, street-level thermal data	Identification of urban heat hotspots for local adaptation (e.g. tree planting, cool surfaces)	Expand urban sensor networks and crowd-sourced temperature data collection
Limited urban morphology and land cover integration in models	Accurate modelling of urban interventions (e.g., green roofs, shading)	Improve representation of built and natural surfaces in climate models
Sparse air quality validation data (esp. during smog episodes)	Real-time, validated air quality data for public health alerts	Densify monitoring networks; integrate citizen-sensing data
Generalized assumptions in thermal comfort	Individualized assessment for vulnerable populations (elderly, children, outdoor workers)	Adjust comfort models for age, activity level, clothing insulation, etc.

indices (e.g., PMV, PMD)		
Limited socio-demographic integration in exposure models	Mapping of socially vulnerable areas for targeted interventions	Overlay social vulnerability data with climate-health indicators
Insufficient representation of indoor exposure	Holistic assessment of heat and air quality risks, especially for homebound individuals	Integrate indoor air/thermal environment data into urban climate-health assessments
Few scenario-based simulations of adaptation/mitigation strategies	Evaluating effectiveness of planned measures (e.g., mobility reduction, urban greening)	Run comparative scenarios under SSPs/RCPs with and without adaptation actions
Fragmented data and modelling systems across sectors	Integrated tools for urban planning, health, environment	Develop interoperable platforms connecting health, climate, and urban planning tools
Complex model outputs not tailored to decision-makers	Usable visual tools (e.g., dashboards, heat-health risk maps) for local authorities	Co-create communication formats with end users (e.g., planners, emergency services)
Lack of short-term forecasts linked to health response protocols	Real-time alerts for emergency and health services during heatwaves and smog	Implement operational short-term modelling with health outcome triggers

5.1.4 Prioritization

The priorities and focus of CSA Prague can be summarized in Table .

Table 4: Prioritization and focus of CSA Prague

Priority	Focus
Climate-health early warnings	Real-time protection of human life (heatwaves/smog)
High-resolution risk mapping	Street/neighbourhood-level data to support local adaptation
Equity and vulnerability integration	Ensuring inclusive and just climate resilience
Usability of tools for decision-makers	Making science actionable for policy and planning

To fulfil the priorities above, we could consider the following measures:

- Develop and deploy user-friendly climate-health dashboards
- Launch alert systems for heatwaves and smog (leveraging existing forecast data)
- Start integration of vulnerable population data into current risk maps
- Run future adaptation simulations under various scenarios
- Strengthen inter-agency data integration and governance

5.1.5 Recommendations

Hereby we list some of the recommendations addressing aspects of CSA Prague.

Table 5: Recommendations for CSA Prague

Aspects	Issues	Recommendations
Enhance Urban Climate Monitoring and Modelling	Sparse high-resolution urban data; weak validation of simulations	• Expand urban canopy parameterization in PALM, WRF and COSMO-CLM models to better represent Prague's heterogeneous built and green infrastructure. • Improve modelling of mean radiant temperature and wind exposure at pedestrian level for public comfort and safety. • Validate simulations with empirical microclimate and pollution datasets, including from ALADIN and ATEM systems.
Develop Real-Time Decision Support and Early Warning Tools	Gaps in real-time public health and adaptation response	• Co-create heatwave and smog early warning systems, integrating UTCI, AQI, and epidemiological data. • Link forecasts (e.g. from WRF, ALADIN) to predefined public health protocols, such as ambulance deployment, public cooling centers, or targeted alerts to vulnerable groups. • Develop user-friendly dashboards and visual maps for municipal planners and emergency services
Integrate Health and Socio-Demographic Vulnerability in Risk Assessment	Lack of social equity in current modelling; health risk blind spots	• Include age, income, housing conditions, and occupation data in climate-health exposure maps. • Use emergency call-out data to correlate heat exposure with real-time health outcomes by location. • Incorporate indoor thermal comfort and exposure modelling, especially for elderly and homebound individuals during extreme weather.

Advance Scenario-Based Urban Adaptation Planning	Limited simulations of intervention effectiveness	- Run WRF and PALM-based urban adaptation scenarios simulating greening, albedo changes, mobility reduction, and zoning policies. - Couple regional and local models to assess the future scenario for Prague. - Evaluate the impact of urban interventions on heat exposure, pollutant dispersion, and energy demand under future climate conditions.
Foster Data Sharing, Training, and Stakeholder Co-Creation	Institutional silos; low usability of complex tools	- Establish an urban climate-health data hub integrating weather, pollution, land use, and health data across agencies. - Provide training workshops for planners, health officials, and emergency services to interpret model outputs and dashboards. - Involve local stakeholders in tool design and scenario planning, ensuring outputs match real-world decision-making timelines and formats.

5.2 CSA Leipzig

5.2.1 Inventory of Existing Climate Scenarios and Tools

CSA Leipzig assesses climate related risks, particularly wildfire, heatwave and urban flooding and supports adaptation planning by providing detailed climate hazard insights, targeting adaptations and resilience strategies through risk assessments and stakeholders-driven priorities.

The climate and meteorological model WRF-ARW is applied for weather and climate simulations for Leipzig. WRF-ARW model is driven by ERA5 reanalysis and assesses for both historical and future scenarios at 6 km grid over Leipzig. The hydrological model LISFLOOD receives meteorological inputs from WRF-ARW and assesses flood risks at the resolution of 1 arcminute. The NOAA/BEYOND ML MODEL receives inputs from WRF and predicts daily wildfire risks at five warning categories. Other models for urban adaptation and planning are also involved, for example, UrbanGreenEye (urban heat, hydrology and flood monitoring), PREFERRED (wildfire prediction), ASIMOV (wildfire detection and prevention), Water-Sensitive City (urban water cycle) and CUT – Digital Twin (urban digital twin platform).

5.2.2 Gap Analysis

A gap analysis for CSA Leipzig highlights key limitations affecting climate risk assessment and adaptation planning. The lack of historical wildfire burned area maps impedes the identification of fire-prone zones and validation of risk models, limiting the development of early warning and prevention strategies. Existing wildfire forecasts lack fine-scale resolution (1–2 km), reducing the effectiveness of public safety alerts and local risk communication. Urban climate models

insufficiently incorporate urban form, land use, and surface materials, hindering accurate heat island mapping and the strategic placement of cooling infrastructure. Data on retrofitting costs and building-level thermal comfort are also lacking, restricting cost-benefit evaluations of adaptation measures such as cool roofs and passive cooling. In the context of urban flooding, limited drainage data and permeability mapping constrain the planning of sponge city infrastructure. Finally, fragmented modelling of heat, flood, and fire hazards limits integrated, cross-sectoral spatial planning, underscoring the need for a unified multi-hazard platform.

5.2.3 Gap-Need Mapping

Table 6: Gap need mapping including corresponding stakeholder need and priority action for CSA Leipzig

Gap	Stakeholder Need	Priority Action
Lack of historical wildfire burned area maps	Need for understanding fire-prone zones and validating risk models	Develop targeted early warning and fire prevention policies
No fine-scale fire risk forecasts (1–2 km)	Operational alerts for public safety and emergency preparedness	Enhance data resolution for local decision making and risk communication
Limited integration of urban form, land use, and surface materials in models	Accurate heat island mapping and cool infrastructure planning	Improve siting of cooling centres, parks, reflective surfaces
Lack of retrofitting cost data and building-level comfort indicators	Assessment of adaptation measures (e.g. cool roofs, passive cooling)	Make cost-benefit evaluations for building interventions
Insufficient urban drainage data and permeability mapping	Upgrade planning for drainage systems and sponge city infrastructure	Design and prioritize flood-resilient investments
Fragmented hazard models (separate fire, flood, heat systems)	Demand for integrated multi-hazard platform for spatial planning	Support on decision-making and information exchange over multiple sectors

5.2.4 Prioritization

The priorities and focus of CSA Leipzig can be summarized as follows:

Table 7: Prioritization and focus of CSA Leipzig

Top Priority Cluster	Focus
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Fine-scale wildfire & heat forecasting	to improve public warnings and firefighting readiness
Integrated multi-hazard modelling	to break down silos between hazard-specific planning
Urban flood model upgrades	to inform investment in drainage systems and sponge city design

To fulfil the priorities above, we could consider the following measures:

- Develop a common GIS platform for viewing wildfire, flood, and heat maps interactively.
- Build a modular, open-source modelling architecture that allows stakeholders to plug in new data or adjust assumptions.
- Provide training sessions and user guides for municipal users and planners.

5.2.5 Recommendations

Table 8: Recommendations for CSA Leipzig

Aspects	Issues	Recommendations
Forecast resolution	Current WRF-ARW outputs at 6 km are too coarse for local-scale risk planning	Downscale WRF-ARW outputs to 1–2 km resolution to improve wildfire, heat, and flood predictions
Wildfire Data Gaps	Lack of historical burned area maps and ecosystem/fuel data	Compile burned area datasets (2010–2024) and vegetation maps from satellites and forest inventories
Wildfire Modelling	Limited predictive accuracy due to insufficient event history	Train and calibrate NOA/BEYOND ML model using historical fire events, wind, drought, and heatwave triggers
Public Communication	Low community awareness and engagement with risk information	Launch a public-facing risk platform with daily maps, early warnings, and adaptation tips
Climate Scenario Planning	Planning lacks long-term	Generate future hazard scenarios (2020–2050) under different SSP pathways for urban planning and zoning

	projections under climate change	
Data Sharing & Coordination	Fragmented data sources and institutional silos	Establish a regional data-sharing agreement among municipalities, researchers, and civil protection bodies

5.3 CSA Funen-Odense

5.3.1 Inventory of Existing Climate Scenarios and Tools

The modelling framework for CSA Funen-Odense focuses on assessing climate-related risks such as storms, flooding, and coastal erosion, with the goal of estimating future multi-hazard risks, identifying vulnerable areas, and supporting cost-benefit evaluations of adaptation measures. The hydrodynamic model Delft3D-FLOW is used to simulate extreme storm surge events under multiple RCP scenarios and historical conditions (1969–2004), using dynamically downscaled data from various CMIP5 global climate models. Economic impacts are analysed through the DTU Flood-Damage Cost model, which provides fine-scale assessments, down to the building and parcel level, of direct and indirect losses across residential, industrial, transport, health, and recreational sectors. For surface water modelling, tools such as SCALGO Live, KAMP, and Kystplanlægger simulate hydrological processes at municipal or metre-scale resolution. The modelling system integrates hourly atmospheric forcing from ERA5-Land (0.1°), as well as long-term gridded datasets such as CERRA (5.5 km, since 1984) and E-OBS (12 km, since 1950) to inform simulations. Supplementary inputs include tide-gauge and water-level station data from local ports, crowd-sourced flood photos, and socio-economic layers, all of which support comprehensive and locally relevant impact assessments for Funen and the Odense region.

5.3.2 Gap Analysis

A gap analysis for CSA Funen-Odense highlights several key limitations affecting risk modelling and adaptation planning. The absence of high-resolution wind projections for extreme events restricts local hazard preparedness; generating near-surface wind fields under SSP scenarios is a priority. Sea level rise projections for inland Danish waters, including Odense Fjord, are lacking, limiting flood modelling consistency and long-term planning; downscaling CMIP6-based scenarios is needed. A better understanding of compound flooding from storm surge, rainfall, and river discharge is essential for integrated risk assessments. Historical flood events (e.g. 2006, 2013, 2023) remain under-modelled, though stakeholders value event-based validation using reanalysis and crowd-sourced data. Fragmented tools with inconsistent formats reduce usability in municipal planning; standardizing outputs and metadata would improve integration. Socio-economic indicators linked to cultural heritage, tourism, and business impacts are sparse and should be added to risk maps. Finally, limited use of community-reported flood data and low user capacity for complex tools call for better citizen integration, visual dashboards, and targeted training.

5.3.3 Gap-Need Mapping

Table 9: Gap-Need mapping including corresponding stakeholder need and priority action for CSA Funen-Odense

Gap	Stakeholder Need	Priority Action
Lack of high-resolution future wind speed & direction data for extreme events	Urban planners, emergency services, and infrastructure managers need localized wind hazard projections	Generate hourly/sub-daily near-surface wind fields under SSP1-2.6, SSP2-4.5, and SSP3-7.0
Missing sea level rise (SLR) projections for Danish inland waters	Municipal flood modelers and port authorities need consistent SLR values for long-term planning	Downscale SLR projections for Odense Fjord and inland lowlands using updated CMIP6/SSP scenarios
Limited understanding of compound flood risks (storm surge + rain + river)	Emergency responders and climate adaptation teams need multi-source event simulation for integrated risk maps	Develop multi-hazard flood scenarios combining storm surge, rainfall, and river flow data
Lack of event-scale modelling for key historical floods (e.g. 2006, 2013, 2023)	Local planners and risk communication teams want validation of models based on real, recognizable events	Reconstruct high-impact historical events using ERA5, crowd-sourced data, and reanalysis
Fragmentation of tools (SCALGO, KAMP, DTU, etc.) with inconsistent formats or metadata	Municipalities and regional planners require harmonized outputs for use in standard GIS and planning platforms	Standardize output formats (e.g. GeoTIFF/NetCDF with agreed metadata) and coordinate with tool vendors
Sparse impact indicators tied to cultural heritage, tourism, or economic disruption	Heritage agencies, insurers, and tourism boards need context-aware flood impact estimates	Add socio-economic exposure layers (e.g. cultural assets, business zones) to flood risk maps
Incomplete integration of citizen and crowd-sourced flood data	Local governments want better validation and awareness using community-reported flood evidence	Design portal or form to capture community-reported flooding and integrate into model validation
Low awareness or capacity to use complex datasets/tools	Practitioners (especially smaller municipalities) need interpretable visualizations and training	Develop user guides, dashboards, and host capacity-building workshops using real CSA data

5.3.4 Prioritization

The priorities and focus of CSA Funen-Odense can be summarized as follows:

Table 10: Prioritization and focus of CSA Funen-Odense

Priority	Focus
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Future wind-storm climatology (SSP1-2.6/2-4.5/3-7.0, ≤ 3 km)	Immediate design levels for dikes, harbour quays, high-voltage lines (investments > €500 M locked in 2026). Feeds directly into surge modelling, damage costs and the insurance event set.
Local sea-level-rise curves inside Odense Fjord & straits	Affects freeboard in all structural measures and heritage retrofits.
Coupled compound-event inundation rasters	Single most requested product by municipalities and citizens (“water-on-my-plot”).
Extreme rainfall DDF curves	Strong effect on urban pluvial-flood depth.

To fulfil the priorities above, we could consider the following measures:

- Lock in wind-storm and SLR data
- Deliver compound inundation maps
- Tackle groundwater, DDF curves and the insurance event set

5.3.5 Recommendations

Table 11: Recommendations for CSA Funen-Odense

Aspect	Issue	Recommendation
Sea Level Rise Projections	Lack of localized SLR projections for Odense Fjord and surrounding inland waters	Downscale SLR estimates for mid- and end-century using CMIP6/SSP scenarios tailored to regional topography
Compound Flooding	Current models often isolate storm surge or rainfall	Develop integrated compound flood scenarios combining storm surge, rainfall, and river discharge
Historical Event Validation	Need for model credibility through real-world validation	Reconstruct and simulate 2006, 2013, and 2023 storm surge events using reanalysis and crowd-sourced data
Tool Integration	Fragmentation across tools (DTU, SCALGO, KAMP, Kystplanlægger) and data inconsistencies	Standardize outputs (formats, units, metadata) and promote interoperability through coordinated workflows
Cultural & Economic Exposure	Flood impacts on cultural heritage and economic zones are underrepresented	Add land use and cultural/economic asset layers to damage and exposure models
Crowd-sourced Data	Valuable citizen-reported data not yet fully leveraged	Build simple reporting tools (mobile/web forms) and incorporate these data for validation and storytelling
Data Usability & Capacity	Smaller municipalities lack expertise to use complex datasets and tools	Provide user-friendly dashboards, tutorials, and training sessions targeting local decision-makers

Stakeholder Engagement	Risk of top-down modelling with limited local input	Involve local planners and agencies iteratively in co-design, review, and application of tools
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5.4 CSA Athens

5.4.1 Inventory of Existing Climate Scenarios and Tools

The modelling framework for CSA Athens focuses on assessing the climate hazard of extreme heat and heatwaves, with particular attention to heat stress impacts on vulnerable groups such as the elderly, children, and individuals with pre-existing health conditions. The core model applied is the high-resolution WRF-ARW model, configured at a 1 km spatial resolution and coupled with an urban canopy model (UCM) to simulate urban heat island effects, land-atmosphere interactions, and local-scale climate dynamics. This modelling setup enables detailed analysis of urban thermal environments and supports the planning of targeted countermeasures. The framework is supported by a range of observational datasets. The Hellenic National Hydrological and Meteorological Service (HNMS) provides in-situ meteorological data from ground-based weather stations, while hourly METAR reports serve both for model validation and near-real-time observation. ERA5-Land reanalysis offers comprehensive climate variables, such as temperature, humidity, radiation, and soil moisture, at a 9 km resolution since 1981. In addition, the CERRA reanalysis product contributes long-term regional climate data for trend analysis and model evaluation. These datasets are further complemented by crowdsourced meteorological observations, which enhance spatial granularity and support the validation of simulated urban heat patterns. Collectively, this framework provides a robust basis for evaluating urban heat risks and informing heat adaptation strategies in the Athens metropolitan area.

5.4.2 Gap Analysis

The gap analysis for CSA Athens identifies several limitations in modelling, monitoring, and stakeholder usability that constrain effective heat risk management. Current urban climate models lack sufficient spatial resolution to capture fine-scale variations in dense, heterogeneous areas; upgrading the WRF model to sub-kilometre resolution using detailed urban morphology and land-use data would improve local risk mapping, as described in Spyrou et al., 2024. The absence of real-time operational tools for extreme heat limits emergency preparedness; developing an early warning system combining WRF outputs, METAR reports, and crowdsourced data would support rapid response and alert systems. Existing heat indicators are weakly linked to health outcomes, impeding the definition of actionable thresholds; co-developing health-based indicators such as tropical nights or wet-bulb globe temperature (WBGT) with health authorities is a key need. Current models do not fully capture the cooling effects of NBS; simulating past extreme heat events (e.g. 2021, 2023) with and without interventions like green roofs would provide needed evidence. Observation coverage across the city remains sparse and uneven, particularly in hotspots and vulnerable zones; expanding sensor networks using mobile, satellite, and citizen-contributed data would address this. Finally, many tools are not tailored to end-user needs;

developing accessible interfaces alongside local staff and offering training workshops would strengthen local capacity for heat adaptation planning.

5.4.3 Gap-Need Mapping

Table 12: Gap need mapping including corresponding stakeholder need and priority action for CSA Athens

Gap	Stakeholder Need	Priority Action
Limited spatial resolution in urban climate models	High-resolution risk mapping in dense, heterogeneous urban zones	Upgrade WRF-UCM model to sub-kilometre scale using detailed urban morphology and land-use data
Lack of real-time operational heatwave tools	Short-term forecasts for emergency response and city alert systems	Develop real-time early warning system (EWS) using WRF + METAR + crowdsourced data
Weak links between heat indicators and health outcomes	Health-based thresholds for risk alerts and planning	Co-develop heat-health indicators (e.g., tropical nights, WBGT) with public health authorities
Current NBS effects not fully captured in models	Evidence on the benefits of green infrastructure and cooling strategies	Simulate 2021 & 2023 heatwaves with/without NBS (e.g., green roofs) to quantify urban cooling impact
Sparse and uneven urban observation coverage	Better spatially resolved monitoring in hotspots and vulnerable zones	Expand sensor network with mobile, crowdsourced, and satellite-derived temperature/humidity observations
Tools not designed for local users	Stakeholder-friendly platforms for scenario analysis and decision-making	Co-develop interfaces with local staff; offer training and capacity-building workshops

5.4.4 Prioritization

The priorities and focus of CSA Athens can be summarized as follows:

Table 13: Prioritization and focus of CSA Athens

Top Priority Cluster	Focus
Urban Heat Risk and Early Warning	Develop localized heat indicators (e.g. hot nights, WBGT, CDD) for risk assessment Build operational Early Warning Systems (EWS) for heatwaves and health alerts Integrate thresholds with civil protection and health agency protocols
High-Resolution Climate Modelling	Model WRF-ARW + Urban Canopy to sub-kilometre resolution Improve input data: urban coverage and distribution, land use, albedo, vegetation

	Validate model outputs with high-density observational and remote-sensing data
Nature-Based Solutions (NBS) Assessment	Simulate 2021 and 2023 heatwaves with/without NBS interventions Evaluate cooling, energy demand reduction, and comfort gains from green roofs, urban parks Support urban planning with quantified NBS impacts
Data Accessibility and Scenario Diversity	Provide key variables in user-friendly formats (GeoTIFF, CSV, shapefiles) Enable scenario comparisons through dashboards and visual tools Expand beyond RCP8.5 to include SSP1-2.6 and SSP2-4.5 for policy-relevant planning
Stakeholder Co-Design and Capacity	Co-develop indicators, tools, and thresholds with local actors Deliver training workshops for municipal, health, and emergency services Align outputs with the Athens Climate Action Plan and Heat Health Action Plan

5.4.5 Recommendations

Table 14: Recommendations for CSA Athens

Aspect	Issue	Recommendation
Urban Climate Modelling	Limited resolution and detail in existing WRF-ARW simulations	Refine WRF to sub-kilometre resolution using high-detail urban morphology (i.e. the Agathangelidis, et al., 2019 updated urban dataset) and land use inputs
Heat Risk Indicators	Lack of localized, actionable metrics for extreme heat	Develop and validate urban-specific indicators (e.g., hot nights, CDD, WBGT) for heat-health planning
Early Warning Systems (EWS)	No operational system for short-term heatwave response	Create real-time EWS based on WRF + observational data, linked to civil protection and health agencies
Wind and Ventilation Modelling	Poor resolution of urban airflow and cool corridors	Enhance wind modelling at neighbourhood scale to support planning of cool ventilation paths
Urban Observational Data	Sparse sensor coverage in vulnerable and dense areas	Expand urban observational network with fixed, mobile, and crowdsourced sensors
Stakeholder Capacity	Low engagement and limited tool usability	Conduct co-design workshops and provide training for municipal, health, and planning staff
Policy Integration	Climate tools not embedded in local planning mechanisms	Align indicators and scenarios with Athens Climate Action Plan and Heat Health Action Plan

5.5 CSA Barcelona

5.5.1 Inventory of Existing Climate Scenarios and Tools

The modelling framework for CSA Barcelona integrates climate, wildfire, and drought modelling tools with high-resolution observational data and scenario-based risk assessments to support adaptation planning in a densely populated Mediterranean urban region. Core climate data are derived from CORDEX-CMIP5 regional climate models, with ongoing efforts to refine outputs for urban-scale applications. Wildfire risk is assessed using PREVINCAT modelling tools, supported by static risk and vulnerability maps provided by the Government of Catalonia. Drought conditions are evaluated using indicators such as the SPEI and consecutive dry days, although there are noted gaps in projecting drought duration and severity under future scenarios. High-resolution meteorological observations from EMO-1 and MeteoCat stations support the calibration and validation of model outputs. The risk assessment framework incorporates a combination of hazard indicators (e.g., fire weather index, temperature, wind speed), exposure metrics (e.g., proximity of population to forested areas), and vulnerability indicators (e.g., elderly populations, low-income communities). Scenario analyses are based on RCP2.6, RCP4.5, and RCP8.5 trajectories, focusing on the 2025–2050 time frame. A key reference event for model evaluation is the 1994 Collserola wildfire. Despite the available tools, data gaps remain, particularly in fire regime characteristics such as burned area and fire intensity, as well as in reliable drought severity projections, limiting comprehensive multi-hazard risk assessments.

5.5.2 Gap Analysis

The gap analysis for CSA Barcelona highlights key limitations that hinder effective climate risk management and adaptation planning. The absence of urban-scale climate projections limits assessment of intra-urban variability; downscaling CORDEX-CMIP5 data with urban morphology is needed. Drought duration and severity projections are missing, constraining water resource planning; SPEI-based modelling under RCPs should be integrated. Static wildfire maps offer little seasonal or real-time value; dynamic maps using forecasts and vegetation indices would support emergency services. Missing fire regime data, such as burned area and spread rate, limits fire behaviour modelling; historical reconstructions and future simulations using PREVINCAT tools are necessary. Socioeconomic vulnerability remains underrepresented; spatial mapping of exposed groups and hazard overlays would support targeted action. Incomplete exposure layers, especially near forest edges and critical infrastructure, require refinement. Many datasets remain in non-operational formats; user-friendly dashboards and GIS platforms are needed. Finally, the lack of seasonal early warning tools and misalignment with policy timelines underscores the need to synchronise risk outputs with local adaptation planning cycles.

5.5.3 Gap-Need Mapping

Table 15: Gap need mapping including corresponding stakeholder need and priority action for CSA Barcelona

Gap	Stakeholder Need	Priority Action
Lack of urban-scale climate projections	High-resolution, city-scale data to assess intra-urban climate variability (e.g., heat islands)	Downscale CORDEX-CMIP5 data to urban grid; integrate land use and urban morphology
No drought duration/severity projections	Long-term drought indicators for water planning and agricultural risk	Model SPEI-based drought duration under RCP scenarios; integrate into water supply models
Absence of dynamic wildfire risk maps	Seasonal or real-time risk assessments for civil protection and emergency services	Develop dynamic, time-sensitive risk maps using meteorological forecasts and vegetation indices
Missing fire regime data (e.g., spread rate, flame length, burned area)	Fire behaviour modelling and impact assessments for risk planning	Reconstruct historical fire regimes; simulate future fire behaviour with PREVINCAT tools
Limited integration of socioeconomic vulnerability	Targeted support for elderly, low-income, and migrant populations in exposed areas	Map vulnerable populations spatially; overlay with hazard zones for risk-based prioritization
Incomplete exposure maps (e.g., infrastructure near forests)	Identification of communities and assets at direct wildfire risk	Update and refine exposure layers for <500m forest proximity, critical infrastructure
Data in non-operational or scientific formats	Easily interpretable outputs for planners and decision-makers	Develop dashboards, GIS-based platforms, and standardized risk indicator templates
Lack of early warning tools for seasonal risks	Advance notice for droughts, heatwaves, wildfires to guide preparedness	Create operational seasonal outlook tools with tailored alerts and risk levels
Misalignment of data with policy/planning timelines	Timely input for municipal adaptation plans and emergency updates	Synchronize modelling outputs with policy cycles (e.g., 2025–2030 strategy updates)

5.5.4 Prioritization

The priorities and focus of CSA Barcelona can be summarized as follows:

Table 16: Prioritization and focus of CSA Barcelona

Top Priority Cluster	Focus
Urban-Scale Climate and Hazard Modelling	Downscaling climate models to urban scale; integrating urban morphology and land use into projections for heat, drought, and wind impacts
Wildfire Risk and Fire Regime Analysis	Development of dynamic wildfire risk maps; modeling fire spread, intensity, flame length; reconstructing historical fire regimes for calibration
Drought Monitoring and Forecasting	Improved projections of drought duration and severity; linkage with water resource planning; operational drought monitoring tools
Socioeconomic Vulnerability and Exposure Mapping	Detailed mapping of vulnerable groups and critical infrastructure near forests; integration into multi-hazard risk assessments
Decision Support and Usability	Development of user-friendly dashboards, GIS tools, and standardized outputs; policy-relevant formats for local and regional planning bodies
Seasonal Early Warning and Planning Tools	Operational tools for anticipating heatwaves, droughts, and wildfire seasons; alignment with seasonal planning and emergency preparedness
Policy and Planning Alignment	Ensuring modelling outputs and indicators are timed with local adaptation planning cycles (e.g., 2025–2030); integration into city resilience strategies

5.5.5 Recommendations

Table 17: Recommendations for CSA Barcelona

Aspect	Issue	Recommendation
Climate Modelling	Current models lack urban-scale resolution	Downscale CORDEX-CMIP5 models using urban land use, elevation, and building density data to reflect intra-urban climate variability
Wildfire Risk Assessment	Static maps do not capture real-time or seasonal changes in risk	Develop dynamic wildfire risk maps incorporating real-time meteorological data and vegetation indices
Fire Regime Data	Missing historical data on fire spread, intensity, and burned area	Compile and digitize historical wildfire events (e.g., 1994 Collserola fire); integrate PREVINCAT fire behaviour tools for projections
Drought Projections	No reliable future projections for drought severity and duration	Extend drought modelling with SPEI-based projections under multiple RCP scenarios; link to water management systems

Exposure and Vulnerability Mapping	Lack of integration of socioeconomic vulnerability and infrastructure data	Map vulnerable populations (e.g., elderly, low-income) and critical assets within 500m of forested zones for risk prioritization
Data Usability	Scientific formats are not suitable for planners and local decision-makers	Develop user-focused dashboards, downloadable GIS layers, and summary indicators tailored for municipal stakeholders
Early Warning Systems	No tools to provide lead time for droughts, heatwaves, or wildfire seasons	Implement seasonal forecasting tools with scenario-based alerts for civil protection and planning departments
Policy Integration	Misalignment between modelling timelines and planning cycles	Schedule data delivery and scenario updates to coincide with local adaptation strategy milestones (e.g., 2025–2030 plans)

5.6 CSA Bologna

5.6.1 Inventory of Existing Climate Scenarios and Tools

The modelling framework for CSA Bologna combines regional climate projections, urban microclimate modelling, and socio-environmental indicators to support climate resilience planning in the metropolitan area. High-resolution climate simulations are produced using regional climate models such as COSMO-CLM and ICON-CLM, which provide projections of temperature, precipitation, and other key variables. At the urban scale, ENVI-met enables detailed 3D microclimate modelling to assess thermal comfort, heat stress, and the effectiveness of local adaptation measures. Climate extremes indices are derived using the CLIMPACT2 R package, while adaptation decision support is facilitated through the UrbanProof Toolkit, tailored to municipal needs. The modelling system integrates diverse observational datasets, including satellite data, the Eraclito database, and high-resolution environmental monitoring from ARPAE. This includes Urban Heatwave Thermal Index (UHTI) maps and socioeconomic deprivation indicators, allowing for a multi-dimensional assessment of climate risks. Key indicators tracked include urban heat island (UHI) metrics such as UHTI, PET (Physiological Equivalent Temperature), and PMV (Predicted Mean Vote), as well as air quality indices, heatwave frequency and intensity, and multi-hazard indicators such as Cooling Degree Days (CDD). Simulations primarily focus on the 2030–2050 time frame, with possible extensions to the end of the century, and aim to integrate climate, air quality, and public health data to inform locally relevant adaptation strategies.

5.6.2 Gap Analysis

The gap analysis for CSA Bologna identifies several limitations in data integration, spatial resolution, and operational usability that hinder effective adaptation planning. Fine-scale projections of urban heat island (UHI) effects under future scenarios are lacking; localized UHI models for 2030–2050 using COSMO-CLM and ENVI-met, calibrated to urban morphology, are needed. Current models insufficiently integrate heatwave, air quality, and vulnerability data; co-

developing composite health risk indicators such as UHTI + AQI maps would enhance local risk awareness. Decision tools remain complex or fragmented; expanding the UrbanProof Toolkit with GIS-based dashboards would support municipal planners. Data outputs are often inconsistent or non-operational; standardizing formats (GeoTIFF, NetCDF, shapefiles) and metadata is essential. Trend monitoring of UHI and heatwaves is limited; generating continuous indicators like tropical nights and Cooling Degree Days (CDD) from 2000 to 2050 would inform long-term planning. Energy demand under extreme heat remains uncertain; modelling CDD across sectors can guide infrastructure needs. Air quality-health indices tailored to Bologna's urban context are missing; integrating ARPAE and satellite data with demographic layers would fill this gap. Finally, recent extremes such as the July 2024 heatwave require timely high-resolution simulation, and sectoral data silos should be bridged through shared, multi-hazard datasets linking health, air quality, and energy indicators.

5.6.3 Gap-Need Mapping

Table 18: Gap-Need mapping including corresponding stakeholder need and priority action for CSA Bologna

Gap	Stakeholder Need	Priority Action
Lack of fine-scale UHI projections under future climate scenarios	High-resolution urban climate projections for planning	Develop localized UHI models for 2030–2050 using COSMO-CLM/ENVI-met calibrated to urban morphology
Limited integration of heatwave, air quality, and vulnerability data	Composite risk indicators that reflect coupled hazards and health risks	Co-develop UHTI + AQI health vulnerability maps for urban districts
Insufficient user-friendly decision tools for local planning	Accessible, intuitive platforms for municipal staff and adaptation planners	Expand UrbanProof Toolkit or interface with GIS-based dashboards
Fragmented data formats and inconsistent access	Standardized, interoperable outputs for GIS, planning, and emergency response	Provide model outputs in GeoTIFF, shapefile, and NetCDF formats with metadata
Low visibility of continuous UHI-heatwave trends	Time series analysis of climate-health coupling for monitoring trends	Generate continuous indicators (e.g. tropical nights, PET, CDD) for 2000–2050
Uncertainty in energy demand impacts from future heatwaves	Predictive indicators for cooling energy demand and infrastructure planning	Model Cooling Degree Days (CDD > 5) under multiple scenarios for critical sectors
Absence of a local-scale air quality-health index	Air quality metric tailored to Bologna's urban morphology and health sensitivity (AQI)	Design AQI integrating ARPAE data, satellite products, and demographic vulnerability layers
Need for timely input for health and emergency planning (e.g. 2024 HW)	Rapid assessment of recent/extreme events with high spatial resolution	Simulate July 2024 heatwave event with UHI and health exposure layers

Siloed sectoral data on health, energy, and environment	Integrated, cross-sectoral risk data to inform adaptation strategies	Create shared multi-hazard datasets combining health, air quality, and energy indicators
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5.6.4 Prioritization

The priorities and focus of CSA Bologna can be summarized as follows:

Table 19: Prioritization and focus of CSA Bologna

Top Priority Cluster	Focus
Urban Heat and Health Risk Mapping	Development of high-resolution UHI indicators (e.g. UHTI, PET, PMV) integrated with demographic and health vulnerability data for targeted adaptation planning.
Composite Multi-Hazard Indicators	Creation of indicators combining heatwave intensity, air quality (AQI), and health exposure, especially for elderly populations and socioeconomically vulnerable areas.
High-Resolution Climate Projections	Downscale climate projections (2030–2050) for temperature, humidity, wind, and UHI effects at the neighbourhood scale, supporting heat stress response and urban design.
Decision Support and Visualization Tools	User-friendly platforms (e.g. UrbanProof, GIS dashboards) to support scenario analysis, communication, and local decision-making.
Energy Demand and Cooling Risk Analysis	Modelling of Cooling Degree Days (CDD) to estimate future energy needs and plan for heat-resilient infrastructure and building retrofits.
Timely Event-Based Analysis	Rapid modelling and assessment of specific events (e.g. July 2024 heatwave) to support emergency response, communication, and future preparedness.
Standardization and Interoperability	Delivery of climate and risk data in standardized formats (e.g. GeoTIFF, shapefile, NetCDF) for integration into existing planning systems and cross-sector use.

5.6.5 Recommendations

Table 20: Recommendations for CSA Bologna

Aspect	Issue	Recommendation
Climate Modelling	Lack of fine-scale UHI projections under future climate scenarios	Use downscaled regional models (e.g. COSMO-CLM, ENVI-met) to simulate UHI at neighbourhood resolution
Health Risk Mapping	Fragmented data on heat exposure and health vulnerability	Integrate UHI indicators with demographic, health, and deprivation data to map thermal risk zones

Multi-Hazard Indicators	No single index for combined heat, air quality, and energy risks	Develop composite indices (e.g. UHTI + AQI + CDD) to support public health and planning responses
Decision Support Tools	Limited usability of existing platforms for municipal adaptation planning	Expand or adapt UrbanProof to include new indicators, interactive maps, and sector-specific filters
Energy Demand Forecasting	Uncertainty about future cooling demand in extreme heat events	Model Cooling Degree Days (CDD > 5) under future scenarios to inform energy and infrastructure planning
Air Quality Monitoring	Need for localized air quality-health metric	Co-design an enhanced Air Quality Index (AQI) that reflects local urban and health conditions
Timely Risk Assessment	Lack of high-resolution data for recent extreme events	Simulate and document recent events (e.g. July 2024 heatwave) to inform immediate and long-term planning
Cross-Sector Coordination	Climate, health, and energy data are siloed	Establish shared data repositories and regular coordination mechanisms among key local institutions

5.7 CSA Brasov

5.7.1 Inventory of Existing Climate Scenarios and Tools

The modelling framework for the Brasov Metropolitan Area (BVMA) integrates regional and urban-scale climate, hydrological, and vulnerability assessments to support adaptation planning in a diverse mountain-urban environment. High-resolution regional climate models such as WRF and ICON-CLM provide kilometre-scale simulations of temperature, precipitation, and snow cover. For urban climate analysis, the PALM-4U model enables detailed investigation of heatwaves and urban heat island dynamics. Hydrological modelling focuses on flood risks and water resource assessments related to the Sacele reservoir, incorporating long-term observational data from 1981 to 2024 and high-resolution terrain and land cover datasets. Key climate indicators, such as the SPEI, Water Exploitation Index Plus (WEI+), snow cover metrics, and flood frequency data, are routinely applied. Socioeconomic vulnerability is assessed using demographic and tourism data, helping to identify exposed populations and critical sectors. While the existing modelling system is robust, several gaps persist: high-resolution future projections of snow cover are lacking, flood damage maps require updates, and fine-scale vulnerability mapping for heatwaves and high-resolution digital elevation models remain incomplete. Addressing these gaps is essential for a comprehensive and locally tailored adaptation strategy.

5.7.2 Gap Analysis

The gap analysis for CSA Brasov highlights several key limitations in climate, hydrological, and vulnerability modelling that constrain effective risk-informed adaptation planning. The lack of high-

resolution snow cover projections limits planning for the snow-dependent tourism sector; developing kilometre-scale forecasts with snow depth and snow-making thresholds for 2020–2050 is a priority. Flash flood mapping is outdated and incomplete, hindering infrastructure design and emergency preparedness; updated extent maps based on recent events (e.g. 2018, 2023) should be integrated with land use and exposure data. Fine-scale vulnerability assessments to heatwaves are also missing; detailed risk maps using PALM-4U, PET/UTCI metrics, and demographic overlays are needed to support targeted adaptation. Real-time hydrological monitoring remains limited, especially for the Tărlung basin and Olt tributaries; expanding sensor networks for discharge, soil moisture, and water quality would improve operational water management. Scenario planning tools are often not user-friendly; interactive dashboards with GIS layers for climate indicators and land use projections would enhance stakeholder engagement. Seasonal climate-water balance tools are also lacking, limiting early warning capacity for water scarcity; tailored models for the Săcele reservoir and Braşov metropolitan area are needed. Finally, multi-hazard risk assessments remain fragmented; an integrated platform combining heat, drought, and flood data with land use and population dynamics is essential for coordinated regional planning.

5.7.3 Gap-Need Mapping

Table 21: Gap need mapping including corresponding stakeholder need and priority action for CSA Braşov

Gap	Stakeholder Need	Priority Action
Lack of high-resolution future snow cover projections	Snow-dependent tourism sector needs seasonal and long-term forecasts for planning ski seasons and artificial snow use	Develop km-scale snow cover projections under climate scenarios (2020–2050) with snow depth, snow-making thresholds
Limited data on flood extent and damage for flash floods	Urban planners and emergency responders need accurate flood mapping for risk reduction and infrastructure design	Update flash flood extent maps using recent events (e.g. 2018, 2023), integrate with land use and population exposure data
No fine-scale vulnerability mapping to heatwaves	Municipal authorities need to identify vulnerable populations and urban hotspots for targeted adaptation	Produce detailed heat risk maps using UHI modelling (PALM-4U), demographic overlays, Sky view factor raster and PET/UTCI metrics
Incomplete real-time hydrological monitoring	Water managers require live data for reservoir operations and drought response	Expand sensor networks in Tărlung basin and Olt tributaries for discharge, soil moisture, and water quality (e.g., turbidity)
Lack of urban-scale, user-friendly tools for scenario planning	Stakeholders need accessible platforms to visualize climate risks and test adaptation strategies	Develop interactive dashboards with GIS layers for climate indicators, flood zones, and land use projections

Insufficient climate and water balance tools at seasonal scale	Reservoir operators and planners need early warning on water scarcity risks	Create seasonal water supply-demand balance models for the Sacele reservoir and wider BVMA
Gaps in multi-hazard integration (heat, drought, floods)	Authorities require comprehensive risk assessments for integrated planning	Develop a multi-hazard risk platform combining climate, hydrology, land use, and population data under future scenarios

5.7.4 Prioritization

The priorities and focus of CSA Brasov can be summarized as follows:

Table 22: Prioritization and focus of CSA Brasov

Top Priority Cluster	Focus
Snow and Water Scarcity Management	High-resolution snow cover projections; seasonal water balance models for Sacele reservoir; drought monitoring and water demand-supply scenarios to support tourism and water utilities
Flood Risk and Flash Flood Preparedness	Updated flood extent and damage mapping; real-time hydrological monitoring; flood risk integration in urban planning; early warning systems for flash floods
Heatwave and Urban Climate Resilience	Fine-scale vulnerability mapping for heat exposure; urban heat island modelling; thermal comfort indicators (PET, UTCI); targeted adaptation for vulnerable populations
Integrated Decision Support Tools	Development of user-friendly GIS-based platforms and dashboards; scenario testing for multi-hazard risks; interoperability with urban master plans and land use systems
Data Accessibility and Interoperability	Standardized data formats (GIS-ready); real-time data access (APIs/web platforms); integration of climate, hydrological, and socioeconomic datasets for holistic risk assessment

5.7.5 Recommendations

Table 23: Recommendations for CSA Brasov

Aspect	Issue	Recommendation
Snow Cover & Tourism	Lack of high-resolution snow cover projections for future planning	Develop fine-scale (1-3 km) snow projections under multiple climate scenarios to assess natural snow reliability and artificial snowmaking feasibility

Water Resources	Uncertainty in seasonal water availability and increasing demand from tourism, agriculture, urban management and residents	Implement water demand–supply balance models and monitor inflow/outflow dynamics for the Săcele reservoir and Olt River tributaries
Flood Risk Management	Incomplete mapping of recent flash flood events and lack of damage assessment	Update flood extent and impact maps using data from 2018, 2023, and 2025 events; link flood risks to infrastructure, land use and population exposure
Heatwave Impact	Limited information on vulnerable populations and metropolitan hot spots	Generate fine-scale urban heat risk maps using UHI models, UTCI/PET indicators, and demographic vulnerability overlays
Real-Time Monitoring	Limited real-time hydrological and climate data coverage	Expand sensor networks for discharge, soil moisture, temperature, and precipitation; enable real-time data access for local agencies
Urban Planning Integration	Climate data not aligned with urban planning systems	Provide climate indicators and risk layers in GIS-compatible formats (GeoTIFF, shapefiles) for integration into master plans and zoning tools
Decision Support Tools	Fragmented access to data and lack of interactive tools	Develop a centralized, web-based dashboard for visualizing climate risks (heat, flood, drought) and testing adaptation scenarios
Multi-Hazard Risk Management	Siloed analysis of individual hazards	Create integrated multi-hazard risk maps combining climate, hydrology, land use, and social vulnerability layers for cohesive planning
Tourism Sector Adaptation	No operational tools to anticipate climate stress on ski tourism	Create a tourism-climate dashboard with forecasts of snow reliability, heat extremes, and climate thresholds affecting visitor experience
Data Gaps for Future Projections	Missing long-term high-resolution projections for key hazards	Prioritize downscaling of regional climate projections for the 2020–2050 period to inform sectoral adaptation strategies

5.8 CSA Birmingham

5.8.1 Inventory of Existing Climate Scenarios and Tools

The modelling framework for CSA Birmingham integrates climate modelling, land surface and hydrological simulation, observational data, and urban-specific vulnerability analyses to support adaptation to pluvial flooding, extreme heat, and seasonal climate risks. Key models include JULES (Joint UK Land-Environment Simulator), which simulates land-atmosphere exchanges, and model simulations using a range of land surface and climate scenarios, used to evaluate probabilities of extreme weather events under different climate and land cover scenarios. Observational data are sourced from the UK Met Office and GIS-based flood risk maps provided by the UK Environment Agency. The influence of different tree cover and climate scenarios are assessed with the JULES model using detailed urban tree inventories from Birmingham TreePeople and Birmingham City Council, combined with scenarios of tree cover. Risk

assessments leverage the Birmingham Climate Risk and Vulnerability Assessment (CRVA), as well as pluvial flood hazard maps, heat stress indicators, and other vulnerability indicators, including compound risks such as potential for drain blockage during heavy rainfall. Despite this comprehensive approach, critical gaps persist in availability of high-resolution meteorological station and drainage infrastructure data.

5.8.2 Gap Analysis

The gap analysis for CSA Birmingham reveals several limitations affecting the precision, integration, and usability of climate risk information. Despite the availability of JULES land surface modelled data at relatively high resolution across the CSA, the sparse coverage of meteorological stations and lack of monitored pluvial flood or extreme heat observations across the region to validate the model estimates leaves model uncertainties. Drainage infrastructure data are incomplete, particularly regarding system capacity, age, and condition. Phenology models lack species-specific thresholds, such as base temperatures and degree-day requirements, limiting their utility for urban forestry management; collaboration with researchers to localize these parameters is a priority. Vegetation response to drought is also poorly represented, reducing the accuracy of models for predicting leaf fall and fire hazards; expanding JULES-based simulations and calibrating with historic data would improve realism. Land cover maps need to be compared, and updated if necessary, with the most up-to-date high-resolution datasets from satellite imagery or the UK National Tree Map.

5.8.3 Gap-Need Mapping

Table 24: Gap need mapping including corresponding stakeholder need and priority action for CSA Birmingham

Gap	Stakeholder Need	Priority Action
Lack of regular coverage of meteorological stations to validate the modelled rainfall and heat estimates	Urban planners, infrastructure managers, emergency services need localized risk assessments	Assess the accuracy of JULES rainfall and heat estimates using as many different observations as possible e.g. satellite surface temperatures
Incomplete drainage system data (capacity, age, quality)	Drainage operators and flood risk managers need to predict where systems may fail during storms	Include information where possible and highlight uncertainties where data are not available
Missing tree species-specific phenology thresholds (base temperatures, degree days)	Urban planning teams need to understand variations in tree phenology (leaf fall in particular), to consider implications for maintenance schedules, and tree planting strategy	Provide reasonable ranges for phenology metrics and highlight uncertainties in estimates

Limited data on vegetation response to drought (e.g., leaf fall during dry periods)	City maintenance teams and climate modelers need to assess risk of drain blockages and fire hazards	Provide estimates of uncertainty ranges and highlight where knowledge is very limited
Outdated or coarse land use/land cover maps	Planners and emergency services need updated spatial context for risk prioritization	Acquire or update high-resolution land cover datasets (e.g., UK National Tree Map, satellite data)
Absence of compound hazard scenario tools (e.g., heat + drought + infrastructure failure)	Emergency planning and resilience officers require compound risk modelling	Use JULES to assess scenarios combining multiple stressors using climate, land cover and infrastructure data

5.8.4 Prioritization

The priorities and focus of CSA Birmingham can be summarized as follows:

Table 25: Prioritization and focus of CSA Birmingham

Aspect	Issue	Recommendation
Climate and Hazard Data	Insufficient network of met stations/data for validating urban-scale risk modelling	Use range of available observations for model validation e.g. satellite surface temperature data
Drainage Infrastructure	Outdated, incomplete data on drainage systems and capacity	Use available drainage data and highlight areas of major uncertainty
Vegetation and Phenology	Missing phenological thresholds and drought sensitivity for tree species	Use available observations on tree phenology, consider using satellite vegetation metrics e.g. Leaf Area Index
Flood Risk and Leaf Fall	High pluvial flood risk during seasonal leaf fall exacerbated by drought	Use vegetation models to forecast early/dense leaf fall; coordinate with drainage maintenance schedules
Compound Risk Modelling	Single-hazard focus ignores compound events like heat + drought + flooding	Develop and implement compound scenarios using combined datasets to simulate cascading risks

5.8.5 Recommendations

Table 26: Recommendations for CSA Birmingham

Aspect	Issue	Recommendation
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Climate and Hazard Data	Insufficient high-resolution climate data for urban-scale risk modelling	Use range of available observations for model validation e.g. satellite surface temperature data
Drainage Infrastructure	Outdated, incomplete data on drainage systems and capacity	Use available drainage data and highlight areas of major uncertainty
Vegetation and Phenology	Missing phenological thresholds and drought sensitivity for tree species	Use available observations on tree phenology, consider using satellite vegetation metrics e.g. Leaf Area Index
Flood Risk and Leaf Fall	High pluvial flood risk during seasonal leaf fall exacerbated by drought	Use vegetation models to forecast early/dense leaf fall; coordinate with drainage maintenance schedules
Compound Risk Modelling	Single-hazard focus ignores compound events like heat + drought + flooding	Develop and implement compound scenarios using combined datasets to simulate cascading risks

6. Conclusions

Deliverable 2.1 develops and applies a robust analytical framework to assess climate hazards across eight CSAs in Europe, forming a critical foundation for risk-informed modelling in the CARMINE project. Using harmonised indicators, spatial diagnostics, and integrated assessments of multiple hazards, the work captures the evolving characteristics of climate extremes, specifically heatwaves, droughts, and wet events, and their combined influence. The results reveal significant regional variation in hazard frequency, severity, and occurrence, emphasizing the necessity of tailored, site-specific approaches to climate risk evaluation. These insights directly inform the development of modelling tools and scenario-building activities in subsequent work packages and contribute to the co-creation of actionable climate services that can support local planning and decision-making processes.

The eight CSAs studied in CARMINE represent a diverse and strategically selected cross-section of Europe's climatic, geographic, and socio-economic landscapes. Each CSA encompasses not only a major urban core but also surrounding peri-urban and rural areas, which can play a key role in shaping local climate impacts. These regions differ significantly in their exposure and sensitivity to climate hazards due to varying land use, topographic influences, and climate regimes. The heterogeneity observed across the CSAs highlights the importance of place-based

analysis and modelling approaches that consider the local context in order to produce reliable and relevant information for climate adaptation planning.

The hazard assessment identifies heatwaves as the most consistently observed extreme across all CSAs, with a trend toward increasing frequency, intensity, and duration, particularly in urban and peri-urban areas. Drought conditions are found to be most frequent and intense in Mediterranean and continental settings, although signs of increasing dry spells also appear in temperate areas. Wet events exhibit more spatial variability, often influenced by coastal proximity or orographic effects. Notably, the analysis highlights the growing relevance of compound events, such as concurrent heat and drought or sequences of drought followed by heavy rainfall. These compound hazards are particularly disruptive and require integrated assessment approaches to adequately capture their risk potential. The temporal patterns also reflect a clear shift toward more frequent and more intense extremes over the 1990–2022 reference period, reinforcing the role of ongoing climate change as a driver of escalating hazard conditions.

To quantify climate extremes and their potential impacts, the study uses a consistent set of indices, the Heat Magnitude Day (HMD) index for heatwaves, the Standardized Precipitation Evapotranspiration Index (SPEI) for droughts and wet events, and the Combined Stress Index (CSI) to capture compound hazards. These indices are computed at high spatial and temporal resolution, enabling comparisons both across and within CSAs. The HMD reveals hotspots of heat exposure, while SPEI trends highlight drying patterns and periods of excessive wetness. The CSI provides a synthesised view of where multiple hazards converge, pointing to particularly vulnerable zones. Importantly, these metrics do not merely capture the extremes themselves but allow for interpretation of their interactions and timing, which are critical factors in determining their ultimate impact on sectors such as water, energy, health, infrastructure, and agriculture. This integrated assessment underscores the need for multi-hazard models that can reflect both direct and cascading effects of climate extremes. Hazard indices are collected and documented in detail, addressing the relevant hazards in each CSA.

Beyond characterising climate hazards, the analysis incorporates a range of indicators relevant for understanding disaster risk. These include the CSI, as well as joint analyses between HMD and SPEI that reveal the dominant compound event types in each CSA (e.g., hot-dry, hot-wet). However, risk is not solely a function of hazard: exposure and vulnerability components are also critical and are addressed in subsequent work packages. The results indicate clear regional contrasts: in CSAs such as Athens and Barcelona, heat and drought dominate, whereas in others like Leipzig or Brasov, wet events and hot-wet combinations play a more prominent role. The analysis provides an initial layer for risk assessment that can be expanded through the integration of socioeconomic and infrastructural vulnerability metrics. This foundation supports the transition to comprehensive resilience assessments and the formulation of risk-informed adaptation strategies at metropolitan scale. A long list of Disaster Risk Indices is provided, contributing to the harmonisation in the activities of CARMINE with downstream Tasks (T2.4) and Work Packages.

The modelling framework developed in this deliverable establishes a modular and scalable structure for multi-hazard analysis across diverse regional contexts. It enables the integration of empirical data, spatial modelling, and compound hazard indicators into a coherent system

capable of informing both short-term risk management and long-term adaptation planning. The framework is explicitly designed to interface with other project components. More specifically, WP3 will integrate hazard data with socioeconomic assessments to identify vulnerability and adaptation needs, WP4 will use the data to co-develop Digital Twin simulations of climate risks for each CSA, and WP5 will draw on the full set of outputs to operationalise the Impact-Based Decision Support Service (IDSS), offering interactive tools and scenarios to support policy and planning decisions. The modelling structure emphasises transparency, reproducibility, and interoperability, ensuring that it can support cross-sectoral climate resilience efforts and guide the formulation of evidence-based strategies aligned with European climate adaptation goals.

Overall, the modelling framework presented in this deliverable provides a comprehensive, data-driven foundation for understanding and addressing climate hazards across Europe's metropolitan regions. Its multi-hazard, compound-event orientation ensures analytical rigour, while its integration with socio-economic assessments and digital decision tools ensures practical relevance. The work lays a solid foundation for developing locally tailored, scientifically robust adaptation pathways and risk mitigation strategies that are responsive to the evolving dynamics of climate risk.

7. Relevant Horizon projects

7.1 RAMSES (FP7)

The RAMSES project (2018) addressed the complex interplay between climate change, urban development, and sustainability by developing strategies and tools to help cities adapt, mitigate climate impacts, and promote sustainable growth. Focusing on key urban domains such as infrastructure, governance, and social systems, RAMSES sought to align adaptation and mitigation measures with broader sustainable development goals.

A central challenge tackled by the project was integrating efforts to reduce greenhouse gas emissions with actions that enhance resilience to climate impacts, while supporting economic, social, and environmental sustainability. RAMSES highlighted the value of integrated urban planning and cross-sectoral collaboration, emphasizing cooperation among local governments, communities, businesses, and researchers to develop effective solutions for climate resilience.

Overall, RAMSES delivered valuable insights and practical tools to support cities in meeting the challenges of climate change, contributing to more sustainable and resilient urban futures.

More information available at: <https://cordis.europa.eu/project/id/308497/reporting>

7.1.1 Climate Hazards Studied in RAMSES

The project defines climate hazards „as a potentially damaging physical event, such as a flood or heatwave and future changes in the severity or frequency of such hazards are driven by climate change.” The identified and addressed hazards within RAMSES include:

1. **Heatwaves:** RAMSES addressed the impact of heatwaves on health, emphasizing the need for adaptation strategies to mitigate health risks, especially in vulnerable regions like Skopje and Antwerp.
2. **Coastal Floods:** RAMSES studied the impacts of coastal floods on European cities, developing damage curves and cost estimates to assess adaptation options such as dike construction. It provided a library of coastal flood damage curves for 600 European coastal cities.
3. **Winter Storms:** RAMSES analysed the effects of winter storms on urban areas, conducting a storm-damage model inter-comparison to understand damage characteristics and inform adaptation strategies. It developed a unified approach to damage functions, allowing for a generalized assessment of various hazards.
4. **Urban Heat Island Effect:** RAMSES investigated the urban heat island effect and its impact on local climate conditions. It assessed the potential of urban green infrastructure, such as trees and grass, to mitigate the heat island effect and improve thermal comfort in cities, emphasizing judicious placement and design of green infrastructure.
5. **Pluvial Flooding:** RAMSES studied pluvial flooding caused by extreme rainfall events, developing city-scale methods for climate risk assessment and adaptation planning. It simulated impacts on transport networks and explored adaptation options, including green, grey, and soft measures to reduce flood risk and economic disruption.

7.1.2 Climate Impacts Addressed in RAMSES

The project tackled numerous climate impacts through innovative methodologies and comprehensive assessments:

1. **Health Impacts:** Health impacts of heat under different climate scenarios in cities like Skopje and Antwerp were examined, estimating potential increases in mortality rates and associated health costs (considers mortality & morbidity impacts due to outdoor thermal comfort).
2. **Productivity loss due to thermal conditions:** The Antwerp pilot case analysed, amongst others, the heat effect on work productivity. Heat-related productivity losses reflect reduced performance in schools and workplaces due to inadequate indoor thermal comfort.

In conclusion, the Antwerp Pilot highlighted the importance of evaluating the effectiveness of adaptation options and monitoring climate events that impact work productivity, such as absences and days off. These factors are essential components and provide necessary input for the design of evidence-based adaptation pathways.

3. **Coastal Floods and Storms:** RAMSES employed empirical approaches to assess coastal flood and winter storm damage, incorporating theoretical considerations. By developing damage curves and protection cost curves, the project estimated potential damage and adaptation costs for European coastal cities. This data-driven approach

facilitated cost-benefit analyses and informed decision-making for coastal resilience measures.

4. **Impacts on transportation infrastructure:** “Any impacts from extreme weather events on transport infrastructure has the potential to have knock-on effects on city populations and across multiple economic sectors. These impacts can be both direct (in terms of damage to the infrastructure itself and the cost of reconstruction) and indirect (in terms of the disruption to the functioning of the urban economy as the result of the damage). RAMSES looked at ways of assessing the direct and indirect impacts of extreme rainfall events and pluvial flooding on the transport networks in cities, developing tools and models to estimate the economic cost of such disruptions”.
5. **Economic costs:** RAMSES developed a framework for assessment of economic costs and benefits of adaptation, with methodologies developed to consider both direct and indirect costs of climate-related impacts. The framework evaluates the economic consequences of disease and injuries resulting from climate-related health outcomes as well as costs emerging from infrastructure damage.

7.1.3 Hazard Indicators used in RAMSES

1. **Number of heat wave days and rate by which heat wave days are increasing until the end of the century:** RAMSES utilized projections of future urban climate to assess the expected increase in the number of heat wave days, which is anticipated to rise substantially by the end of the century. This indicator provides valuable insight into the changing climate patterns and the heightened risk of heat-related impacts on urban populations and infrastructure.
2. **Health costs, cost-benefits and/or cost-effectiveness of health adaptation:** RAMSES analysed the economic costs associated with health impacts resulting from climate change, particularly focusing on the cost-effectiveness of health adaptation measures. This indicator helps policymakers understand the financial implications of health-related climate impacts and the potential benefits of investing in adaptation strategies to mitigate these costs.
3. **(Extreme) rainfall events and pluvial flooding:** RAMSES investigated the occurrence of extreme rainfall events and subsequent pluvial flooding, using tools like the CityCAT (Glenis, 2018) model to simulate floodwater depths and assess the impact on urban transport networks. By analysing these events, RAMSES aimed to quantify the economic costs of disruptions to transport infrastructure caused by pluvial flooding, providing valuable insights for adaptation planning and risk management in cities.

7.1.4 Climate Models in RAMSES

UrbClim – Urban Climate Model

Development and Purpose

UrbClim (De Ridder, 2015) is an urban climate model developed within the RAMSES (FP7) project

to provide efficient, high-resolution simulations of urban boundary layer climates. Designed for use at the scale of urban agglomerations and their immediate surroundings, UrbClim enables long-term modelling and the generation of relevant climate statistics at the city scale.

Spatial Resolution and Coverage

UrbClim's spatial resolution is typically set at 250 meters, a resolution finer than many other urban climate models. This fine resolution allows UrbClim to accurately represent urban-rural contrasts and the spatial heterogeneity within urban areas. The typical model domain covers an area of about 30 km x 30 km, which is sufficient to capture the key urban and peri-urban processes for medium-sized cities. In the vertical direction, 20 levels were specified, with the first level 10 m above the displacement height, the resolution smoothly decreasing upward to 250 m at the model top located at 3 km height (De Ridder et al. 2015). This vertical resolution allows the model to simulate the vertical structure of the urban atmosphere, including the boundary layer and its interactions with urban surfaces (De Ridder et al. 2015).

Input Data and Forcing

UrbClim uses various data sources to initialize and run its simulations:

- **Urban Land Cover:** Derived from high-resolution datasets such as CORINE Land Cover for European cities and MODIS Land Cover Type data for non-European cities. These datasets provide detailed maps of urban and vegetation cover fractions at resolutions up to 100 meters.
- **Vegetation Cover:** Derived from the Normalized Difference Vegetation Index (NDVI) data obtained from the MODIS instrument, providing a detailed map of vegetation cover fractions at 250 meters resolution.
- **Meteorological Forcing:** The model is forced with synoptic-scale meteorological data from sources like the ECMWF ERA-Interim archive, which provides global coverage at a spatial resolution of 0.75° and a temporal resolution of three hours. This high-resolution forcing data ensures that the model can capture diurnal cycles and large-scale atmospheric dynamics.

Model Evaluation and Performance

The performance of UrbClim (De Ridder et al. 2015) has been validated in several European cities. For example, studies over cities like Toulouse, Ghent, Antwerp, and Bilbao have shown that UrbClim can replicate observed urban heat island effects, canopy temperatures, and wind speed effectively. This validation demonstrates that the model, despite its simplifications, performs comparably to more complex models while being computationally efficient (De Ridder et al., 2015).

Example Outputs and Climate Scenarios

During the second phase of the RAMSES project, UrbClim was coupled with Global Climate Models (GCMs) from the IPCC/CMIP5 archive to conduct long simulations representing present (1986-2005) and future (2081-2100) climate conditions under the RCP8.5 scenario. This coupling

allowed for detailed urban climate projections, providing insights into future urban climate conditions and helping in the development of adaptation strategies (RAMSES Final Report, p. 8).

Other models used within RAMSES

ENVI-met Model

Purpose: ENVI-met is a 3D microclimate modeling software designed to simulate surface-plant-air interactions in urban environments over a small scale, typically from a few meters to several kilometers.

Problem Addressed: ENVI-met addresses the issue of urban heat islands, air quality, and thermal comfort in cities. It helps in understanding how different urban designs, vegetation, and building materials impact local microclimate and human comfort.

Further Information available on the Official Website: <https://www.envi-met.com/>

Damage-functions for Different Hazards

Purpose: The damage-function approach within the RAMSES project aims to quantify the relationship between various climate change-induced hazards (e.g., floods, storms, heatwaves) and the resulting damage to urban infrastructure and human health. This approach helps in understanding and predicting the economic and social impacts of these hazards, facilitating better planning and adaptation strategies for cities.

Problem Addressed: The damage-function approach within the RAMSES project aims to address the intensified impacts of climate change-induced hazards on urban infrastructure and human well-being. By quantifying the economic losses and understanding the dynamics of damage across various hazards, it supports informed decision-making for adaptation and risk management strategies. Through storm-damage model inter-comparisons and the generalization of damage functions for different hazards, the project seeks to enhance the accuracy and applicability of damage assessments. Additionally, by linking floodwater depth simulations with urban transport infrastructure, the project aims to estimate the disruption costs associated with extreme events, aiding in the development of resilient urban systems.

Further Information are available on: <https://cordis.europa.eu/project/id/308497/reporting>

CityCAT Model – A Model to Estimate the Economic Cost of Disruptions in Transport Infrastructure

Purpose: The model serves to simulate urban flooding scenarios and assess their impacts on transport infrastructure. It can model the movement of water through urban areas during heavy rainfall events. It aims to provide a comprehensive understanding of flood risk in urban areas by integrating spatial data on transport networks with detailed simulations of pluvial floodwater depths.

Problem Addressed: Urban flooding poses significant challenges to transportation systems, leading to disruptions and economic losses. The CityCAT-Model (Glenis, 2018) addresses this

problem by enabling the estimation of disruption costs associated with flood events, facilitating the development of strategies to enhance the resilience of urban transport infrastructure to extreme weather events. It provides insights into vulnerable areas and supports the design of resilient urban drainage systems.

Further Information available: <https://cordis.europa.eu/project/id/308497/reporting> & Glenis et al. (2018)

7.1.5 Data Gaps

No data gaps have been identified.

7.1.6 Risk Evaluation

City-Scale Vulnerability and Risk Assessment: RAMSES conducted city-scale risk assessments to understand current and future climate-related hazards. By combining top-down and bottom-up approaches, the project evaluated risks from heatwaves, droughts, floods, and extreme rainfall events across European cities. RAMSES developed tools to estimate economic costs and assess adaptation options, enabling cities to enhance resilience and mitigate climate impacts effectively.

EU-wide or global datasets which provide information on both the climate hazard, and the exposure and vulnerability aspects of risk:

Urban Audit: The Urban Audit dataset provides comprehensive information on various aspects of urban areas across Europe, including demographics, infrastructure, and socio-economic indicators. It covers all 571 EU Urban Audit cities and serves as a valuable resource for understanding the characteristics and vulnerabilities of urban areas.

- Area Covered: European Union Urban Audit cities:
<https://ec.europa.eu/eurostat/en/web/gisco/geodata/statistical-units/urban-audit>

Globcover30: Globcover30 is a global land cover dataset that provides detailed information on land cover types and changes. It offers valuable insights into the spatial distribution of land cover classes, which is essential for assessing exposure and vulnerability to climate-related hazards.

- Area Covered: Global coverage: http://due.esrin.esa.int/page_globcover.php

EU DEM (Digital Elevation Model): The EU DEM is a digital elevation dataset that provides detailed information on the topography of European regions. It offers elevation data at high resolutions, which is crucial for assessing flood risk and understanding the terrain's influence on hazard exposure.

- Area Covered: European Union regions:
<https://ec.europa.eu/eurostat/web/gisco/geodata/digital-elevation-model/eu-dem>

European Climate Assessment & Dataset Programme: The European Climate Assessment & Dataset Programme provides climate data and analyses for the European region. It includes

historical climate observations, future climate projections, and related information, which are essential for assessing climate hazards and impacts.

- Area Covered: European region: <https://www.ecad.eu/>

WorldClim Climate Observations: WorldClim provides global climate data layers, including temperature and precipitation, at different spatial resolutions. These data are invaluable for understanding climate patterns, variability, and trends, which are essential for assessing climate risks and impacts.

- Area Covered: Global coverage:
https://www.worldclim.org/data/index.html#google_vignette

However, those datasets provide only a limited number of variables or reported at low resolutions. Some countries and cities, however, have bespoke datasets on climate hazards, vulnerability, or exposure, which could allow more detailed analysis. Two approaches were developed in RAMSES, therefore, to provide risk assessment tools that take advantage of *the best available* data, providing a transferable and comparable platform for risk assessments:

1. A **top-down**, data-driven indicator approach identified risks across all 571 EU Urban Audit cities.
2. A **bottom-up** detailed ‘systems-based’ assessment of risks for selected case studies.”

Top-Down Approach:

The top-down approach in RAMSES employs a systematic, data-driven methodology to assess climate risks across a broad spatial scale, encompassing all 571 EU Urban Audit cities. It utilizes widely available datasets and indicators to quantify the potential impacts of climate hazards, such as heatwaves, droughts, river flooding, and pluvial flooding, on urban areas. Through climate hazard simulations driven by different scenarios (e.g., Low, Medium, High), the top-down approach evaluates the severity and frequency of future climate-related events, providing insights into the changing risk landscape across Europe.

By integrating measures of vulnerability and exposure derived from various qualitative and quantitative data sources, including population density, land use patterns, and infrastructure characteristics, the top-down approach assesses the adaptive capacity of urban areas to withstand climate impacts. This comprehensive analysis enables policymakers and city planners to prioritize adaptation measures and allocate resources effectively to reduce climate risks at a regional scale. Moreover, the top-down approach facilitates comparisons between different cities and regions, highlighting spatial variations in hazard severity and vulnerability profiles, and informing strategic adaptation planning at the European level.

While the top-down approach offers valuable insights into the overarching climate risks faced by urban areas across Europe, it may overlook the nuances and complexities of individual cities' contexts. Therefore, it serves as a foundational tool for identifying high-level priorities and guiding

broad policy decisions but may require complementation with more detailed, localized assessments for effective implementation of adaptation strategies.

Bottom-Up Approach

In contrast, the bottom-up approach in RAMSES adopts a tailored, context-specific methodology to assess climate risks and develop adaptation strategies for selected case study cities, such as London, Antwerp, and Bilbao. This approach recognizes the unique socio-economic, environmental, and governance dynamics of each city, emphasizing stakeholder engagement and local knowledge integration in the assessment process.

By conducting detailed, systems-based analyses at the city scale, the bottom-up approach considers the intricate interactions between climate hazards, urban infrastructure, and socio-economic factors, capturing the specific vulnerabilities and resilience capacities of individual cities. Through scenario-based simulations and participatory workshops with key stakeholders, the bottom-up approach explores a range of potential climate impacts and adaptation options, evaluating their effectiveness and feasibility within the local context.

The bottom-up approach enables a deeper understanding of the spatial patterns of vulnerability and climate impacts within cities, facilitating the identification of priority areas for intervention and the development of targeted adaptation measures. By incorporating input from diverse stakeholders, including local governments, community groups, and businesses, this approach fosters ownership and commitment to adaptation initiatives, enhancing their sustainability and effectiveness over the long term.

While the bottom-up approach provides valuable insights into city-specific climate risks and adaptation pathways, it may require substantial resources and expertise to implement, limiting its scalability to other cities. Therefore, it complements the top-down approach by offering detailed insights into localized vulnerabilities and adaptation needs, which can inform more targeted and contextually appropriate interventions at the city level.

Differences between the two approaches:

- **Scope:** The top-down approach provides a broad assessment of climate risks across multiple cities, while the bottom-up approach focuses on in-depth analysis and adaptation planning for specific case study cities.
- **Data Utilization:** The top-down approach relies on widely available datasets and indicators to assess climate risks, whereas the bottom-up approach incorporates detailed, city-specific data and stakeholder input for a more comprehensive analysis.
- **Scale:** The top-down approach operates at a regional or city-wide scale, facilitating comparisons and strategic planning, while the bottom-up approach zooms in on local-scale impacts and adaptation options, considering the intricacies of individual urban contexts.

More information available at: <https://cordis.europa.eu/project/id/308497/reporting> & <https://cordis.europa.eu/docs/results/308/308497/final1-ramses-final-publishable-summary-report.pdf>

7.2 AXIS (H2020)

The AXIS (Assessment of Cross(X)-sectoral climate Impacts and pathways for Sustainable transformation) program is a Horizon 2020 project linked with the ERA-NET Consortium AXIS a program under the Joint Programming Initiative "Connecting Climate Knowledge for Europe" (JPI Climate). To this effect, AXIS aims to overcome boundaries between science communities through inter- or transdisciplinary research projects. It focuses on assessing the cross-sectoral impacts of climate change and identifying pathways for sustainable transformation. The program aims to enhance understanding of how climate change affects various sectors, such as agriculture, energy, water, and health, and how these impacts interact with each other.

Through interdisciplinary research and collaboration, AXIS seeks to develop innovative methodologies and tools for assessing climate risks and vulnerabilities across different sectors. By integrating scientific knowledge with stakeholder engagement and policy analysis, the program aims to support informed decision-making and adaptation planning at regional, national, and European levels.

The AXIS program contributes to advancing the European Union's climate adaptation agenda by providing evidence-based insights into the interconnected nature of climate impacts and the pathways for building resilience and sustainability in a changing climate. It emphasizes the importance of holistic approaches to climate adaptation that consider the complex interactions between sectors and promote integrated and coordinated responses to climate challenges.

More information available at: <https://cordis.europa.eu/project/id/776608>

The ERA-NET Consortium AXIS (Assessment of Cross(X) - sectoral climate Impacts and pathways for Sustainable transformation) aims to promote cross-boundary, cross-community research with the overall goal to improve coherence, integration and robustness of climate impact research and connect it to societal needs. To this effect, AXIS aims to overcome boundaries between science communities through inter- or transdisciplinary research projects.

7.2.1 Climate Hazards in AXIS

The AXIS program addresses various climate hazards that are anticipated to have significant impacts across sectors and regions. These hazards include extreme weather events like heatwaves, which are becoming more frequent and severe due to climate change, sea-level rise, which threatens coastal communities and ecosystems and changes in precipitation patterns. These climate hazards are assessed to understand their potential impacts and to develop appropriate adaptation strategies.

Extreme Weather Events:

- **Heatwaves:** Prolonged periods of excessively hot weather, which can cause health issues, crop damage, and increased energy demand.
- **Floods:** Overflow of water onto normally dry land, which can result from heavy rainfall, river overflow, or storm surges. Floods can damage infrastructure, disrupt transportation, and lead to loss of life and property.
- **Storms:** Severe weather conditions including thunderstorms, hurricanes, and cyclones, characterized by strong winds, heavy rain, and sometimes hail or tornadoes. These can cause significant structural damage and power outages.
- **Droughts:** Extended periods of deficient rainfall leading to water shortages, which can impact agriculture, water supply, and ecosystems.

Sea-Level Rise:

- Gradual increase in the average level of the world's oceans due to the melting of ice caps and glaciers and the thermal expansion of seawater. This threatens coastal areas with flooding and erosion.

Changes in Precipitation Patterns:

- Variations in the amount, intensity, and frequency of precipitation, which can lead to unpredictable water availability, affecting agriculture and water resources management.

7.2.2 Climate Impacts

In the context of AXIS, “climate impacts” refers to the diverse and multi-faceted effects that climate change has on natural and human systems. These impacts are analyzed across various sectors and scales, encompassing environmental, economic, and social dimensions.

AXIS evaluates climate impacts across multiple sectors such as agriculture, water resources, health, and infrastructure. By integrating biophysical impacts with economic models, the program aims to provide a comprehensive understanding of how climate change affects various aspects of society and the economy.

Agriculture:

- **Crop Yield Reductions:** Changes in temperature and precipitation can adversely affect crop growth and yields, leading to food insecurity.
- **Pest and Disease Spread:** Warmer temperatures and altered precipitation can increase the prevalence of agricultural pests and diseases.

Water Resources:

- **Water Scarcity:** Reduced rainfall and increased evaporation rates can lead to water shortages, impacting drinking water supplies and irrigation.
- **Increased Flood Risk:** Altered precipitation patterns and increased frequency of extreme weather events can lead to more frequent and severe flooding.

Health:

- **Heat-Related Illnesses:** More frequent and intense heatwaves can lead to heat exhaustion and heatstroke, particularly affecting vulnerable populations.
- **Vector-Borne Diseases:** Changes in climate can expand the range and activity period of disease vectors like mosquitoes, increasing the spread of diseases such as malaria and dengue fever.

Infrastructure:

- **Damage from Extreme Events:** Storms, floods, and other extreme events can damage buildings, roads, bridges, and other infrastructure, leading to economic losses and disruption of services.

7.2.3 Hazard Indicators in AXIS

Hazard indicators in the context of the AXIS program are metrics and data points used to quantify and monitor the various climate-related hazards that affect different sectors and regions. By integrating these hazard indicators, AXIS aims to improve the coherence and robustness of climate impact research, aligning scientific findings with societal needs and policy objectives. The focus on cross-sectoral and cross-scale assessments ensures that hazard indicators are relevant to a wide range of stakeholders, from local communities to international policymakers.

The following indicators are used:

Temperature Anomalies:

- Deviations from long-term average temperatures, indicating trends in warming or cooling that can affect various climate-sensitive sectors.

Frequency and Intensity of Extreme Weather Events:

- Metrics track the occurrence and severity of events like heatwaves, storms, and floods, which are critical for risk assessment and adaptation planning.

Hydrological Indicators:

- **River Flow Patterns:** Changes in the flow regimes of rivers, affecting water availability and ecosystem health.
- **Groundwater Levels:** Monitoring changes in groundwater reserves, which are vital for water supply and agricultural irrigation.

In projects like **DIRT-X**, sediment delivery impacts on reservoirs are evaluated using these hydrological indicators to understand the implications for water resources. **CROSSDRO** uses drought frequency and severity metrics to assess cross-sectoral impacts on water supply, agriculture, and ecosystems. **MAPPY** incorporates indicators related to changes in precipitation patterns and their effects on plant diversity and crop yields. **LAMACLIMA** leverages land management indicators to evaluate the effectiveness of various strategies in mitigating climate impacts. These indicators help to create a comprehensive picture of climate hazards, guiding the development of targeted adaptation and mitigation strategies.

More information about each project can be found at:

Joint Programming Initiative Climate. "Projects." Joint Programming Initiative Climate. Accessed June 21, 2024. <https://jpi-climate.eu/project/?wpv-relationship-filter=161>.

7.2.4 Climate Models in AXIS

Different projects within AXIS use climate and impact models. A couple examples are given below:

Example of models used within the BIO-CLIMAPATHS project

LPJmL (Lund-Potsdam-Jena managed Land) model is a dynamic global vegetation model designed to simulate vegetation composition, structure, and the carbon and water cycles in response to climate and land-use changes. It is utilized within the BIO-CLIMAPATHS project to assess the biophysical impacts of climate change on biomass production, helping to understand how different sectors of the bioeconomy, both food and non-food, are affected by climate hazards. The model generates detailed spatial maps that identify climate hazard hotspots and predict biomass losses under various climate scenarios.

MAGPIE (Model of Agricultural Production and its Impact on the Environment) is an economic land-use model that focuses on global agricultural production. It is designed to evaluate the interplay between agricultural practices, economic factors, and environmental impacts. In the context of BIO-CLIMAPATHS, MAGPIE is used to analyse how climate change-induced price shocks in the bioeconomy sectors affect different stakeholders, such as households, farmers, and financial agents. The model also explores the conditions under which distributive effects, such as inequality, might emerge and how they can be mitigated.

Both models provide critical outputs that inform policy recommendations and resilience strategies. LPJmL's outputs include spatially explicit maps of biomass losses and climate hazard impacts, while MAGPIE offers insights into economic impacts and adaptive responses. Together, they enable the BIO-CLIMAPATHS project to develop comprehensive strategies for achieving sustainable and climate-resilient bioeconomy pathways, ultimately contributing to the EU2030 climate and energy targets.

7.2.5 Data Gaps

Based on the AXIS (H2020) program's publications and websites, several (data) gaps have been identified and addressed:

1. **Cross-Sectoral Climate Impact Models:** There is a lack of integration between climate impact models across different sectors.
 - **Addressed by:** AXIS projects like BIOCLIMAPATHS, which developed a cross-sectoral methodology linking climate, crop, socio-economic, and agent-based models to understand the interconnected impacts of climate extremes on crop yields and supply chains.
2. **High-Resolution and Detailed Data:** Insufficient high-resolution climate data for local and regional impact assessments.
 - **Addressed by:** Projects like CROSSDRO, which utilized diverse methodologies including meteorology, hydrology, and remote sensing to analyse drought effects regionally and continentally.
3. **Economic Impact Assessments:** Limited comprehensive economic impact data across sectors.
 - **Addressed by:** Projects such as DIRT-X, which integrated hydrological process models with economic models to assess the economic consequences of water resource impacts on energy production.
4. **Sector-Specific Vulnerabilities and Adaptation Data:** Lack of detailed data on vulnerabilities and adaptive capacities specific to different sectors.
 - **Addressed by:** Projects like LAMACLIMA, which studied the impacts of changes in land cover and management on climate variables, water availability, and heat stress.

7.2.6 Risk Evaluation

- **Vulnerability and Exposure Assessment:**
 - Evaluating the susceptibility of different sectors and regions to climate hazards, considering factors like adaptive capacity and resilience. This involves both current conditions and future projections.
- **Holistic Risk Approach:**
 - Incorporating scientific, economic, and social dimensions to provide a comprehensive evaluation of climate risks. This approach helps in identifying effective adaptation and mitigation strategies.
- **Quantitative and Qualitative Methods:**
 - Using a mix of quantitative data (e.g., climate models, economic assessments) and qualitative information (e.g., expert judgment, stakeholder input) to address uncertainties and enhance the robustness of risk assessments.

7.3 HARMONIA(H2020)

HARMONIA, a project funded by the EU's Horizon 2020 initiative, focuses on enhancing urban resilience and sustainability in the face of climate change and extreme events. Through a collaboration of 22 partners across Europe, including municipalities, NGOs, industry, academia, and research centers, HARMONIA aims to develop a resilience assessment platform. This platform leverages satellite and auxiliary data to provide detailed insights into climate change impacts at the local level, aiding in decision-making for adaptation and mitigation efforts.

The project targets both natural and manmade hazards exacerbated by climate change, such as urban flooding and heat islands. It integrates diverse datasets to create an Integrated Resilience Assessment Platform (IRAP), which acts as a decision support tool for cities and urban stakeholders. HARMONIA's contributions extend to various stakeholders: it helps local authorities assess vulnerability and predict climate-related hazards, supports initiatives to improve quality of life and public health for citizens and NGOs, and fosters knowledge exchange and technological advancements for industry and academia.

Aligned with international frameworks like the Paris Agreement, the Sendai Framework, and the Sustainable Development Goals (SDGs), HARMONIA contributes to global efforts in climate mitigation and disaster resilience. By leveraging existing Earth Observation datasets and services, IRAP enables stakeholders to model various planning options against different climate change scenarios, thus facilitating informed decision-making for building resilient and sustainable communities.

More information available at: <https://harmonia-project.eu/about/>

7.3.1 Climate Hazards

Natural and manmade hazards intensified by CC

- urban flooding
- soil degradation
- geo-hazards (landslides, earthquake, ground deformation)

Manmade hazards and impacts:

- heat islands
- urban heat fluxes
- Air Quality
- Gas emissions

à Sustainable reconstruction of urban areas and the health of humans and ecosystems are therefore top priorities.

Information available at: https://harmonia-project.eu/wp-content/uploads/2022/07/WP1_D1.1_Data_management_plan_v1_30_11_2021_MPL_v02_final.pdf, page 7

7.3.2 Climate Impacts

Temperature Extremes: Increased heat stress on populations and infrastructure due to urban heat islands.

Water Scarcity and Quality: Impacts on water availability and quality due to altered precipitation patterns and contamination from flooding.

Infrastructure Damage: Damage to buildings, roads, and other infrastructure from flooding, landslides, and seismic events.

Health Impacts: Adverse health effects from poor air quality, extreme temperatures, and water contamination.

Ecosystem Degradation: Loss of biodiversity and ecosystem services due to environmental degradation and pollution.

Economic Losses: Increased costs related to disaster response, infrastructure repair, and health care.

7.3.3 Hazard Indicators

Urban Flooding: precipitation patterns, water levels, and floodplain mapping.

Soil Degradation and Geo-hazards: soil stability, erosion rates, landslide susceptibility, and seismic activity.

Heat Islands and Urban Heat Fluxes: temperature variations within urban areas, heat fluxes, and their impact on urban environments.

Air Quality: concentrations of pollutants such as NO₂, PM₁₀, and PM_{2.5}.

Gas Emissions: emissions of greenhouse gases and other pollutants.

Additional Information available at: <https://cordis.europa.eu/project/id/101003517> & <https://cordis.europa.eu/project/id/101003517/reporting/it>

7.3.4 Climate Models in HARMONIA

Overview of the existing climate models used within the HARMONIA project, organized by their application areas. These models leverage a variety of input data sources, such as satellite observations, meteorological data, and in situ measurements, to simulate different physical processes relevant to urban climate and environmental hazards. The output variables provide critical information for assessing and mitigating the impacts of urban air quality, heat islands, temperature anomalies, flash flooding, and geohazards.

Urban Air Quality Services

Model Name	Function	Input Data	Physical Processes Simulated	Output Variables
Sensor Invariant Atmospheric Correction (SIAC)	Atmospheric correction and surface reflectance retrieval	MODIS, Sentinel-2, Landsat data, CAMS atmospheric fields	Data assimilation based on MODIS BRDF and CAMS atmospheric constituents	Surface reflectance, atmospheric constituents with uncertainties
Radiative Transfer Models – ProSAIL and TIP	Simulate radiative transfer through vegetation canopies and atmospheres	Vegetation structure, soil, and atmospheric properties	Light absorption, scattering by vegetation and soil, and atmosphere	Reflectance and transmittance spectra
Dry deposition model (TBD)	Model dry deposition of pollutants	Pollutant concentration, meteorological data	Transport and deposition of pollutants onto surfaces	Deposition velocity and fluxes
Traffic emissions factors (TBD)	Estimate emissions from traffic	Traffic data (vehicle counts, types), emission factors	Emission of pollutants from vehicles	Emission rates for various pollutants

Urban Heat Fluxes & Urban Heat Islands

Model Name	Function	Input Data	Physical Processes Simulated	Output Variables
Local Scale Land Surface Temperature Model (LSLST)	Model land surface temperature	Satellite data, meteorological data	Energy balance at the surface, including radiative and heat fluxes	Land surface temperature
Aerodynamic Resistance Method (ARM)	Estimate heat fluxes from urban surfaces	Surface temperature, meteorological data	Heat transfer between urban surfaces and atmosphere based on aerodynamic resistance	Sensible and latent heat fluxes
Objective Hysteresis Model (OHM)	Model urban heat island effect	Meteorological data, urban surface properties	Heat storage and release in urban materials, temperature variations	Urban heat storage, temperature profiles

Humidity and Temperature Anomalies & Complex Scenarios

Model Name	Function	Input Data	Physical Processes Simulated	Output Variables
Fire Weather Index (FWI)	Assess fire weather conditions	Meteorological data (temperature, humidity, wind speed, precipitation)	Moisture content in fine fuels, fire behaviour based on weather conditions	Fire danger rating, moisture codes, and fire behaviour indices

Urban Flash Flooding

Model Name	Function	Input Data	Physical Processes Simulated	Output Variables
Itzi - distributed hydrologic and hydraulic model	Model hydrologic and hydraulic processes in urban areas	Precipitation, topography, land use, soil characteristics	Surface runoff, infiltration, channel flow, and water movement through urban infrastructure	Flood extents, water depths, flow velocities
ecPoint-Calibrate	Calibrate precipitation forecasts for flood prediction	Precipitation forecasts, observed rainfall data	Statistical correction of precipitation forecasts to improve accuracy	Calibrated precipitation forecasts

Geohazards

Model Name	Function	Input Data	Physical Processes Simulated	Output Variables
Persistent Scatterer Interferometry	Detect ground deformation using satellite radar data	SAR (Synthetic Aperture Radar) data	Ground deformation detection using phase differences in radar signals	Ground displacement maps, deformation time series
Geotechnical models	Assess stability and behaviour of soils and structures	Soil properties, groundwater data, load conditions	Stress-strain behaviour of soils, settlement, slope stability, and other geotechnical processes	Stability assessments, deformation predictions

7.3.5 Data Gaps

The HARMONIA project has identified several key data gaps that need to be addressed to enhance the resilience of urban areas against climate change. These gaps are primarily in the fitness for purpose of some EO (Earth Observation) and modeled datasets for fine spatial scales in urban environments, high-resolution EO data for validation, and in situ data of all kinds.

1. **Fitness for Purpose of EO and Modelled Datasets:** The existing datasets sometimes lack the fine spatial resolution required for detailed urban analysis. This gap affects the ability to accurately model and assess urban climate impacts.
2. **High-Resolution EO Data for Validation:** There is a need for more high-resolution EO data that can be used to validate the models and applications developed within the project. The existing datasets often lack the necessary detail to confirm the accuracy of these models.
3. **In Situ Data:** In situ data, which is crucial for calibration, validation, and operational processes, is often either unavailable or inconsistent. This data varies greatly from one city to another, leading to significant uncertainties and gaps in the models and applications being developed.

Addressing the Data Gaps

The HARMONIA project employs several strategies to address these data gaps:

1. **Linking EO and In-Situ Data:** The project emphasizes the need to effectively integrate EO data with in-situ observations to improve model accuracy and applicability at urban scales. This involves harmonizing data needs across different cities to ensure seamless operation of the applications and decision support systems (DSS) developed by the project.
2. **Downscaling Climate Data:** Downscaling is a critical requirement for the project. It involves translating large-scale climate data to finer urban scales. This process is being addressed through substantial resources dedicated in WP4 (Work Package 4), which focuses on refining models to make them suitable for city neighborhood scales.
3. **AI/ML Techniques:** The project considers the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques, which heavily rely on high-quality training data. This further underscores the demand for high-resolution in situ data for effective model training and validation.

Approaches/Models for Downscaling Climate Data

The HARMONIA project uses several approaches and models for downscaling climate data to the urban scale:

1. **Dynamic Downscaling:** This approach involves using high-resolution regional climate models to downscale data from coarser global climate models. This method provides more detailed climatic projections at urban scales, considering local topography and urban features.
2. **Statistical Downscaling:** Statistical methods are used to develop relationships between large-scale climatic variables and local climate characteristics. This approach can be used to translate coarse-scale projections to finer urban scales based on observed historical data.

3. **Hybrid Approaches:** Combining dynamic and statistical downscaling methods can provide more robust and accurate results by leveraging the strengths of both approaches. These hybrid models can better account for the complex interactions between large-scale climate processes and local urban factors.
4. **AI/ML-Based Downscaling:** Utilizing AI and ML techniques can enhance the downscaling process by automatically identifying patterns and relationships in the data that traditional methods might miss. These techniques can be particularly useful in handling large datasets and improving prediction accuracy at urban scales.

By addressing these data gaps and employing advanced downscaling techniques, the HARMONIA project aims to improve the accuracy and usability of climate impact models for urban areas, thereby enhancing their resilience to climate change.

More information can be found at: https://harmonia-project.eu/wp-content/uploads/2022/07/WP2_D2_3_Requirements-and-availability-on-data-acquisition-transformation-intelligence-extraction_24_12_2021_ASSIMILA.pdf

7.3.6 Risk Evaluation

The HARMONIA programme incorporates a robust risk evaluation framework as part of its Integrated Resilience Assessment Platform (IRAP). This framework leverages Earth Observation (EO) data and advanced modelling tools to provide a comprehensive multi-hazard risk assessment for urban areas. The risk evaluation process is multi-faceted and includes data collection and integration, modelling and simulation, and vulnerability assessment.

Integrated Resilience Assessment Platform (IRAP)

The IRAP developed by HARMONIA is designed to evaluate risks by integrating various datasets from prominent platforms like GEOSS and DIAS. This integration facilitates a holistic approach to assess multi-hazard risk factors effectively.

1. Data Collection and Integration

- The risk evaluation process begins with the collection and integration of satellite and auxiliary data. The HARMONIA project utilizes high-resolution EO data alongside auxiliary datasets to conduct comprehensive analyses. This data integration is crucial for understanding the various environmental and climate-related hazards that urban areas face.
- The integration of these datasets enables the platform to utilize diverse sources of information, enhancing the accuracy and comprehensiveness of the risk assessments.

2. Modelling and Simulation

- Advanced modelling tools are employed within IRAP to predict and simulate potential impacts of various hazards. These tools allow for the detailed analysis and projection of climate change impacts at an urban scale. The modelling efforts

in HARMONIA include the use of dynamic and statistical downscaling techniques to refine climate projections for city neighbourhoods, ensuring that the simulations are relevant at a local level.

- The models consider various factors, including local topography and urban features, to provide realistic simulations of potential hazard impacts. This predictive capability is essential for proactive risk management and resilience planning.

3. Vulnerability Assessment

- An integral part of the risk evaluation process is the vulnerability assessment. This involves identifying and evaluating the susceptibility of urban areas to different climate hazards. The HARMONIA project uses EO data and in situ observations to assess the vulnerability of urban infrastructure, populations, and ecosystems to hazards like extreme temperatures, flooding, and pollution.
- The assessment identifies critical vulnerabilities that need to be addressed to enhance urban resilience. This includes evaluating the structural integrity of buildings, the resilience of infrastructure networks, and the capacity of social systems to respond to and recover from adverse events.

More information available at: <https://harmonia-project.eu/irap/> & <https://harmonia-project.eu/about/>

8. References

- Adrienne Arsht-Rockefeller Foundation Resilience Center, Atlantic Council (2023): Hadrian Aqueduct Cooling District. Heat Risk Reduction Guidelines. <https://onebillionresilient.org/hadrian-aqueduct-cooling-district-heat-risk-reduction-guidelines> [Accessed: 30.11.2024].
- Agathangelidis, I.; Cartalis, C.; Santamouris, M. Integrating urban form, function, and energy fluxes in a heat exposure indicator in view of intra-urban Heat Island assessment and climate change adaptation. *Climate* 2019, 7, 75.
- AXIS (2023): AXIS funded projects' achievements and publications. https://jpi-climate.eu/wp-content/uploads/2024/05/D4.2_Synthesis_Report.pdf [Accessed: 17.07.2025].
- AXIS (2024a): Newsletter "Outcomes of the 10 funded projects under AXIS programme". <https://jpi-climate.eu/wp-content/uploads/2024/01/AXIS-Newsletter-Outcomes-of-the-10-funded-projects.pdf> [Accessed: 17.07.2025].
- AXIS (2024b): Synthesis paper with the impact of the projects and recommendations for follow-up activities, Work Package 4 - Deliverable 4.2. https://jpi-climate.eu/wp-content/uploads/2024/05/D4.2_Synthesis_Report.pdf [Accessed: 17.07.2025].
- Birmingham City Council (2024): Route to Net Zero Annual Report 2023. https://www.birmingham.gov.uk/download/downloads/id/28568/route_to_net_zero_annual_report_2023.pdf [Accessed: 24.10.2024].
- Brousse, O., Georganos, S., Demuzere, M., Dujardin, S., Lennert, M., Linard, C., et al. (2020): Can we use Local Climate Zones for predicting malaria prevalence across sub-Saharan African cities? *Environ. Res. Lett.* 15:124051. doi: 10.1088/1748-9326/abc996.
- Brunner, L., & Voigt, A. (2024): Pitfalls in diagnosing temperature extremes. *Nat Commun* 15, 2087, <https://doi.org/10.1038/s41467-024-46349-x>
- Ceglar, A., Toreti, A., Prodhomme, C., Zampieri, M., Turco, M., & Doblas-Reyes, F.J. (2018): Land-surface initialisation improves seasonal climate prediction skill for maize yield forecast. *Scientific Reports* 8(1). <https://doi.org/10.1038/s41598-018-19586-6>
- Chatzopoulos T., Pérez Domínguez, I., Zampieri, M., & Toreti, A. (2019): Climate extremes and agricultural commodity markets: A global economic analysis of regionally simulated events. *Weather and Climate Extremes* 27, 100193. <https://doi.org/10.1016/j.wace.2019.100193>
- CMCC (2024): COSMO-CLM – Climate Limited-area Modelling Community, <https://www.cmcc.it/models/cosmo-clm-climate-limited-area-modelling-community>.
- CORDIS (2024a): Reconciling Adaptation, Mitigation and Sustainable Development for Cities, <https://cordis.europa.eu/project/id/308497/reporting>,
- CORDIS (2024b): Assessment of Cross(X)-sectoral climate Impacts and pathways for Sustainable transformation, <https://cordis.europa.eu/project/id/776608>.
- Cornes, R., van der Schrier, G., van den Besselaar, E.J.M., & P.D. Jones (2018): An Ensemble Version of the E-OBS Temperature and Precipitation Datasets. *Journal of Geophysical Research, Atmosphere*, 123. <https://doi.org/10.1029/2017JD028200>
- Crausbay, S.; Ramirez, A.; Carter, S.; Cross, M.; Hall, K.; Bathke, D.; Betancourt, J.; Colt, S.; Cravens, A.; Dalton, M.; Dunham, J.; Hay, L.; Hayes, M.; McEvoy, J.; McNutt, C.; Moritz,

M.; Nislow, K.; Raheem, N.; Sanford, T. (2017): Defining ecological drought for the 21st century, *Bulletin of the American Meteorological Society*, 98, <https://doi.org/10.1175/BAMS-D-16-0292.1>.

De Ridder, K., Lauwaet, D., & Maiheu, B. (2015): UrbClim – A fast urban boundary layer climate model. *Urban Climate*, 12, 21–48, <https://doi.org/10.1016/j.uclim.2015.01.001>.

Droogers, Peter & Allen, Richard. (2002): Estimating Reference Evapotranspiration Under Inaccurate Data Conditions. *Irrigation and Drainage Systems*. 16. 33-45. 10.1023/A:1015508322413.

DWD (2024): Urban climate model PALM-4U, <https://www.dwd.de/DE/leistungen/palm4u/palm4u.html> [Accessed: 30.11.2024].

ECMWF et al. (2024): Urban heat islands and heat mortality. Demonstrating heat stress in European cities. <https://stories.ecmwf.int/urban-heat-islands-and-heat-mortality/index.html#:~:text=Temperatures%20rise%20because%20paved%20ground%20absorb%20heat%2C%20buildings,ones%20from%20the%20harmful%20effects%20of%20rising%20temperatures> [Accessed: 25.10.2024].

Emori, S., Taylor, K., Hewitson, B., Zermoglio, F., Juckes, M., Lautenschlager, M., Stockhause, M. (2016): CMIP5 data provided at the IPCC Data Distribution Centre. Fact Sheet of the Task Group on Data and Scenario Support for Impact and Climate Analysis (TGICA) of the Intergovernmental Panel on Climate Change (IPCC), https://www.ipcc.ch/site/assets/uploads/2020/11/TGICA_Fact_Sheet_CMIP5_data_provided_at_the_IPCC_DDC_Ver_1_2016.pdf [Accessed: 31.10.2024].

European Centre for Medium-Range Weather Forecasts et al. (2024): Air quality, climate change and public health - How C3S and CAMS can help protect European citizens, <https://stories.ecmwf.int/air-quality-climate-change-and-public-health/index.html> [Accessed: 25.10.2024].

European Commission, Joint Research Centre (2024): Large Scale Integrated Sea-level and Coastal Assessment Tool. <http://data.jrc.ec.europa.eu/collection/LISCOAST> [Accessed: 30.11.2024].

Ferranti, E., Cook, S., Greenham, S. V., Grayson, N., Fitcher, J., and Salter, K. (2023): Incorporating heat vulnerability into local authority decision making: An open access approach. *Sustainability*, 15, 13501, <https://doi.org/10.3390/su151813501>.

Forest Science and Technology Centre of Catalonia (2024): Fuel models and forest fires behaviour, <https://previncat.ctfc.cat/en/index.html>, [Accessed: 08.11.2020].

Fundit (2018): Call for Proposals. <https://fundit.fr/en/calls/axis-joint-call-proposals-assessment-cross-sectoral-climate-impacts-and-pathways-sustainable>.

Generalitat de Catalunya (2024a): Civil Protection Map of Catalonia. https://interior.gencat.cat/en/arees_dactuacio/proteccio_civil/mapa_de_proteccio_civil/ [Accessed: 08.11.2024].

Generalitat de Catalunya (2024b): Forest fire danger maps. <https://agricultura.gencat.cat/ca/ambits/medi-natural/incendis-forestals/perill-incendi-diari-informe-setmanal/mapa-perill-incendi/> [Accessed: 08.11.2024].

Glenis, V., McGough, A.S., Kilsby, C.G., Kutija, V., & Quinn, P.F. (2018): CityCAT: a high-resolution urban flood modelling tool. *Water Science and Technology*, 77(9), 2371-2382.

Gomes, G., Salamon, P., Carina-Denise, L., Sperzel, T., Radke-Fretz, M., Schweim, C., Ziese, M., Russo, C., & Grimaldi, S. (2025): EMO: A high-resolution multi-variable gridded meteorological data set for Europe. European Commission, Joint Research Centre (JRC) [Dataset] <https://doi.org/10.2905/0BD84BE4-CEC8-4180-97A6-8B3ADAAC4D26> PID: <http://data.europa.eu/89h/0bd84be4-cec8-4180-97a6-8b3adaac4d26>

Hao, Z., Hao, F., Xia, Y., Feng, S., Sun, C., Zhang, X., Fu, Y., Hao, Y., Zhang, Y., & Meng, Y. (2022): Compound droughts and hot extremes: Characteristics, drivers, changes, and impacts. *Earth-Science Reviews*, Vol. 235, p. 104241.

Hao, Z., Singh, V., & Hao, F. (2018): Compound Extremes in Hydroclimatology: A Review. *Water*, 10, <https://doi.org/10.3390/w10060718>.

Harmonia (2021): Requirements and availability on data acquisition, transformation & intelligence extraction. https://harmonia-project.eu/wp-content/uploads/2022/07/WP2_D2_3_Requirements-and-availability-on-data-acquisition-transformation-intelligence-extraction_24_12_2021_ASSIMILA.pdf.

Höppe, P. (1999): The physiological equivalent temperature – a universal index for the biometeorological assessment of the thermal environment, *Int. J. Biometeorol.*, 43, 71–75, <https://doi.org/10.1007/s004840050118>.

IPCC (2023): Sixth Assessment Report (AR6). <https://www.ipcc.ch/assessment-report/ar6/>.

JPI Climate (2024): AXIS Program Details. <https://jpi-climate.eu/programme/axis/>.

LIFE UrbanProof (2018): The URBANPROOF toolkit. A decision support system for assisting municipalities in adaptation planning, <https://tool.urbanproof.eu/sdiurbanareas/?lang=IT> [Accessed: 30.11.2024].

European Commission (2026): LISVAP User Guide. Introduction. https://ec-jrc.github.io/lisflood-lisvap/1_LISVAP_introduction/ [Accessed: 12.05.2026].

Leonard, M., Westra, S., Phatak, A., Lambert, M., van den Hurk, B., McInnes, K., Risbey, J., Schuster, S., Jakob, D., & Stafford - Smith, M. (2014): A compound event framework for understanding extreme impacts. *WIREs Climate Change*, 5, <https://doi.org/10.1002/wcc.252>.

Mahony, C.R., & Cannon, A.J. (2018): Wetter summers can intensify departures from natural variability in a warming climate. *Nature Communications* 9, <https://doi.org/10.1038/s41467-018-03132-z>.

Marin-Ferrer, M., Vernaccini, L., & Poljansek, K. (2017): Index for Risk Management INFORM Concept and Methodology Report — Version 2017, EUR 28655 EN, <https://doi.org/10.2760/094023>.

Martilli, A.; Clappier, A.; Rotach, M.W. An urban surface exchange parameterisation for mesoscale models. *Bound.-Layer Meteorol.* 2002, 104, 261–304.

Martilli, A., Nazarian, N., Krayenhoff, E. S., Lachapelle, J., Lu, J., Rivas, E., Rodriguez-Sanchez, A., Sanchez, B., and Santiago, J. L. (2024): WRF-Comfort: simulating microscale variability in outdoor heat stress at the city scale with a mesoscale model, *Geosci. Model Dev.* 17, 5023–5039, <https://doi.org/10.5194/gmd-17-5023-2024>.

Municipality of Brasov (2024): Planul Urbanistic General al Municipiului Brasov. Elaborarea Formei Preliminare a Planului Urbanistic General al Municipiului Brasov,c

https://www.brasovcity.ro/file-zone/urbanism/pug/consultare/1.%20Piese%20scrise/2.1.1_Memoriu%20general.pdf
[Accessed: 14.12.2024].

National Weather Service (2024): Drought Types. <https://www.weather.gov/safety/drought-types#:~:text=Hydrological%20Drought%20is%20based%20on,and%20ground%20water%20table%20decline> [Accessed: 25.10.2024].

Pham, T. V.; Steger, C.; Rockel, B.; Keuler, K.; Kirchner, I.; Mertens, M.; Rieger D.; Zängl, G.; Früh, B. (2024): ICON in Climate Limited-area Mode (ICON release version 2.6.1): a new regional climate model, <https://doi.org/10.5194/gmd-14-985-2021>.

Ramli, M.W.A., Alias, N.E., Yusop, Z., & Taib, S.M. (2020): Disaster risk index: a review of local scale concept and methodologies. IOP Conference Series: Earth and Environmental Science, 479, 012023, <https://doi.org/10.1088/1755-1315/479/1/012023>.

RAMSES Project (2018): Final Publishable Summary Report. <https://cordis.europa.eu/docs/results/308/308497/final1-ramses-final-publishable-summary-report.pdf>

Raymond, C., Horton, R.M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J., Bowen, S.G., Camargo, S.J., Hess, J., Kornhuber, K., Oppenheimer, M., Ruane, A.C., Wahl, T., & White, K. (2020): Understanding and managing connected extreme events. *Nature Climate Change*, 10, <https://doi.org/10.1038/s41558-020-0790-4>.

Reder, A., Raffa, M. Padulano, R. Rianna, G., Mercogliano, P. (2022): Characterizing extreme values of precipitation at very high resolution: An experiment over twenty European cities, *Weather and Climate Extremes* 35, <https://doi.org/10.1016/j.wace.2022.100407>.

Resler, J., Bauerová, P., Belda, M., Bureš, M., Eben, K., Fuka, V., Geletič, J., Jareš, R., Karel, J., Keder, J., Krč, P., Patiño, W., Radović, J., Řezníček, H., Sühling, M., Šindelářová, A., and Vlček, O. (2024): Challenges of high-fidelity air quality modeling in urban environments – PALM sensitivity study during stable conditions, *Geosci. Model Dev.*, 17, 7513–7537, <https://doi.org/10.5194/gmd-17-7513-2024>.

Riahi et al. (2017): The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview, *Global Environmental Change*, Volume 42, 2017, Pages 153-168, ISSN 0959-3780, <https://doi.org/10.1016/j.gloenvcha.2016.05.009>.

Russo, S., Sillmann, J., and Fischer, E. (2015). Top ten European heatwaves since 1950 and their occurrence in the coming decades. *Environmental Research Letters*, 10(12), 124003. <https://doi.org/10.1088/1748-9326/10/12/124003>.

Salamanca, F.; Krpo, A.; Martilli, A.; Clappier, A. A new building energy model coupled with an urban canopy parameterization for urban climate simulations—Part I. formulation, verification, and sensitivity analysis of the model. *Theor. Appl. Climatol.* 2010, 99, 331–344.

Schäfer, L., Künzel, V., Adil, L., & Eckstein, D. (2025): Methodology of the Climate Risk Index. Germanwatch, <https://www.germanwatch.org/sites/default/files/2025-03/Climate%20Risk%20Index%202025%20Methodology.pdf>.

Serrano-Notivol, R., Beguería, S., & de Luis, M. (2019): STEAD: a high-resolution daily gridded temperature dataset for Spain, *Earth Syst. Sci. Data*, 11, 1171–1188, <https://doi.org/10.5194/essd-11-1171-2019>.

Skamarock, W.C.; Klemp, J.B.; Dudhia, J.; Gill, D.O.; Liu, Z.; Berner, J.; Wang, W.; Powers, J.G.; Duda, M.G.; Barker, D.M.; et al. (2019): A Description of the Advanced Research WRF Model Version 4; National Center for Atmospheric Research: Boulder, CO, USA.

Spyrou, C.; Koukoulas, M.; Saviolakis, P.-M.; Zerefos, C.; Loupis, M.; Masouras, C.; Pappa, A.; Katsafados, P. (2024): Green Roofs as a Nature-Based Solution to Mitigate Urban Heating During a Heatwave Event in the City of Athens, Greece. *Sustainability*, 16, 9729. <https://doi.org/10.3390/su16229729>.

Stewart, I. D., and Oke, T. R. (2012): Local climate zones for urban temperature studies. *Bull. Am. Meteorol. Soc.* 93, 1879–1900. doi: 10.1175/BAMS-D-11-00019.1.

Toreti, A., Cronie, O., & Zampieri, M. (2019): Concurrent climate extremes in the key wheat producing regions of the world. *Scientific Reports*, 9 <https://doi.org/10.1038/s41598-019-41932-5>.

UCAR (2024): Weather Research & Forecasting Model (WRF), <https://www.mmm.ucar.edu/models/wrf> [Accessed: 30.11.2024].

UNDP. Bureau for Crisis Prevention (2004): Reducing disaster risk: a challenge for development—a global report. United Nations. New York: UNDP.

United Nations Economic Commission for Europe (2025): *Set of Core Disaster-Risk-Related Indicators: White Cover Version (March 2025)*. Geneva: UNECE.

Urban, A., Fonseca-Rodríguez, O., Di Napoli, C., & Plavcová, E. (2022): Temporal changes of heat-attributable mortality in Prague, Czech Republic, over 1982–2019. *Urban Climate*, 44 (April). <https://doi.org/10.1016/j.uclim.2022.101197>.

Vousdoukas, M. I.; Mentaschi, L.; Voukouvalas, E.; Verlaan, M.; Feyen, L. (2017): Extreme Sea levels on the rise along Europe's coasts, *Earth's Future* 5:3, <https://doi.org/10.1002/2016EF000505>.

Wahl, T., Jain, S., Bender, J., Meyers, S.D., & Luther, M.E. (2015): Increasing risk of compound flooding from storm surge and rainfall for major US cities. *Nature Climate Change* 5, <https://doi.org/10.1038/nclimate2736>.

WCRP (2018): News Announcement. <https://www.wcrp-climate.org/news/wcrp-news/1327-eu-jpi-climate-s-axis-joint-call-for-transnational-collaborative-research-projects-2018>.

World Data Center for Climate (2023): CORDEX dynamical downscaling data sets based on CMIP5 forcing, https://www.wdc-climate.de/ui/project?acronym=CORDEX_DDS-CMIP5_native-grid [Accessed: 31.10.2024].

World Health Organization: Useful Definitions and Early Warning Information for Natural Hazards, https://cdn.who.int/media/docs/default-source/disaster-mngmt/drm_fact_sheet_early_warning_natural_hazards.pdf?sfvrsn=d2b7dead_1, [Accessed: 25.10.2024].

World Health Organization (2024): Wildfires. https://www.who.int/health-topics/wildfires#tab=tab_1 [Accessed: 25.10.2024].

World Meteorological Organization (2024a): Drought. <https://wmo.int/about-us/world-meteorological-day/wmd-2020/drought#:~:text=Drought%20is%20a%20prolonged%20dry,use%2C%20increase%20vulnerability%20to%20drought>. [Accessed: 25.10.2024].

World Meteorological Organization (2024b): Heatwave. <https://wmo.int/topics/heatwave> [Accessed: 25.10.2024].

Zampieri, M., Ceglar, A., Dentener, F., & Toreti, A. (2017): Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environmental Research Letters*, 12(6), 064008.

Zampieri, M., Garcia, G.C., Dentener, F., Gumma, M.K., Salamon, P., Seguni, L., & Toreti, A. (2018): Surface freshwater limitation explains worst rice production anomaly in India in 2002. *Remote Sensing* 10(2). <https://doi.org/10.3390/rs10020244>.

Zampieri, M., Ceglar, A., Dentener, F., Dosio, A., Naumann, G., van den Berg, M., & Toreti, A. (2019): When will current climate extremes affecting maize production become the norm? *Earth's Future* 7(2):113–122. <https://doi.org/10.1029/2018EF000995>.

Zhang, W., Luo, M., Gao, S., Chen, W., Hari, V., & Khouakhi, A. (2021): Compound Hydrometeorological Extremes: Drivers, Mechanisms and Methods. *Frontiers in Earth Science*, 9, <https://doi.org/10.3389/feart.2021.673495>.

Zscheischler, J., & Fischer, E.M. (2020): The record-breaking compound hot and dry 2018 growing season in Germany. *Weather and Climate Extremes*, 29, <https://doi.org/10.1016/j.wace.2020.100270>.

Zscheischler, J., & Seneviratne, S.I. (2017): Dependence of drivers affects risks associated with compound events. *Science advances*, 3, <https://doi.org/10.1126/sciadv.1700263>.

Zscheischler, J., Westra, S., van den Hurk, B.J.J.M., Seneviratne, S.I., Ward, P.J., Pitman, A., AghaKouchak, A., Bresch, D.N., Leonard, M., Wahl, T., & Zhang, X. (2018): Future climate risk from compound events. *Nature Climate Change*, 8, <https://doi.org/10.1038/s41558-018-0156-3>.

9. Annex

9.1 Seasonal Drought Maps

The maps presented in this annex section illustrate the spatial distribution of key drought characteristics, namely mean drought intensity, calculated over the period 1990–2022 for each grid point within the respective CSAs and for each season. More details on the indicators used can be found at 3.2. Climate Indicators, while descriptions of the annual maps at 3.7. Droughts.

9.1.1 CSA Barcelona

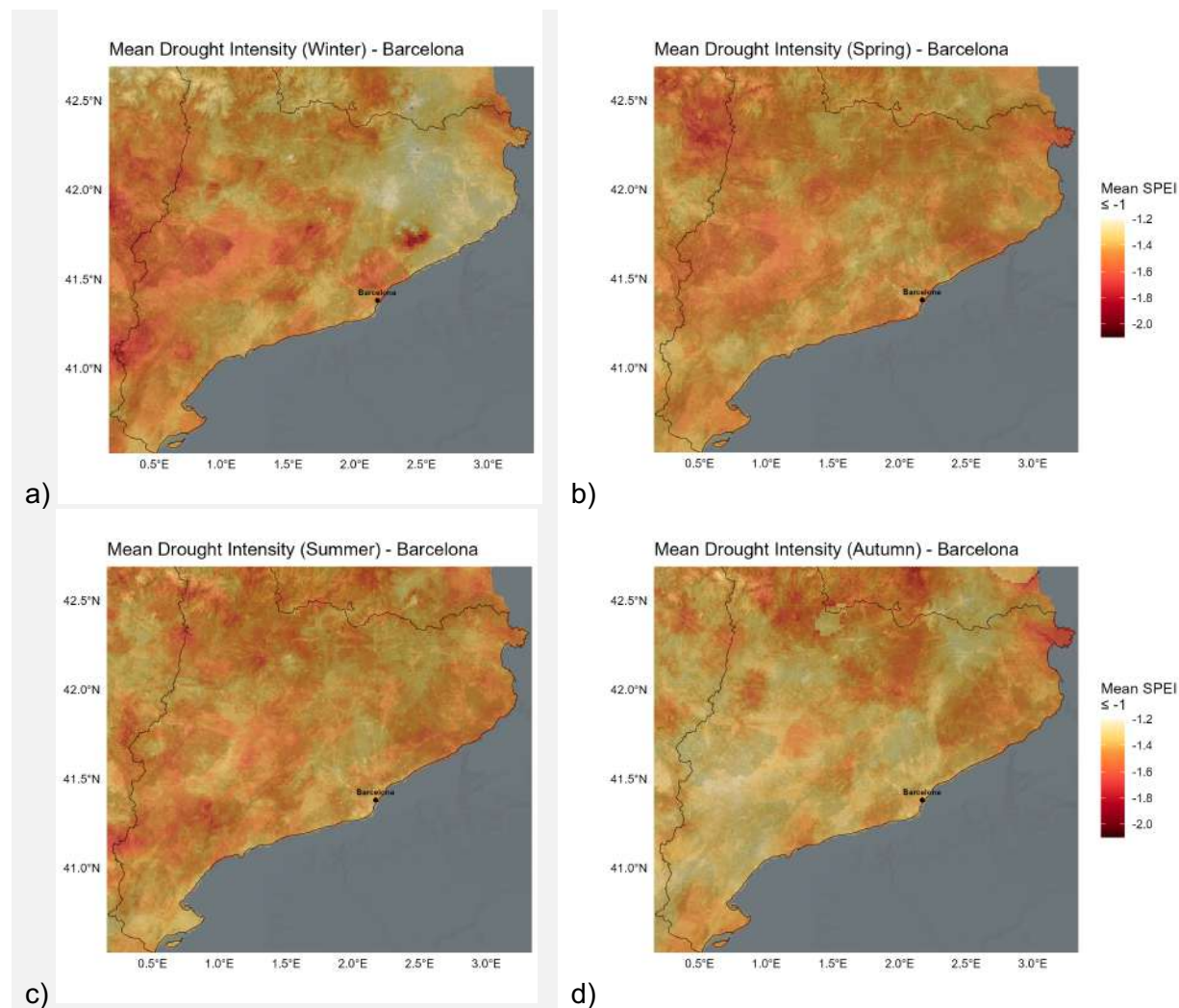


Figure A 1: Spatial distribution of seasonal drought intensity for the greater CSA Barcelona area during 1990–2022 based on the $SPEI-1 \leq -1$ (reference period 1992–2022), showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.1.2 CSA Brasov

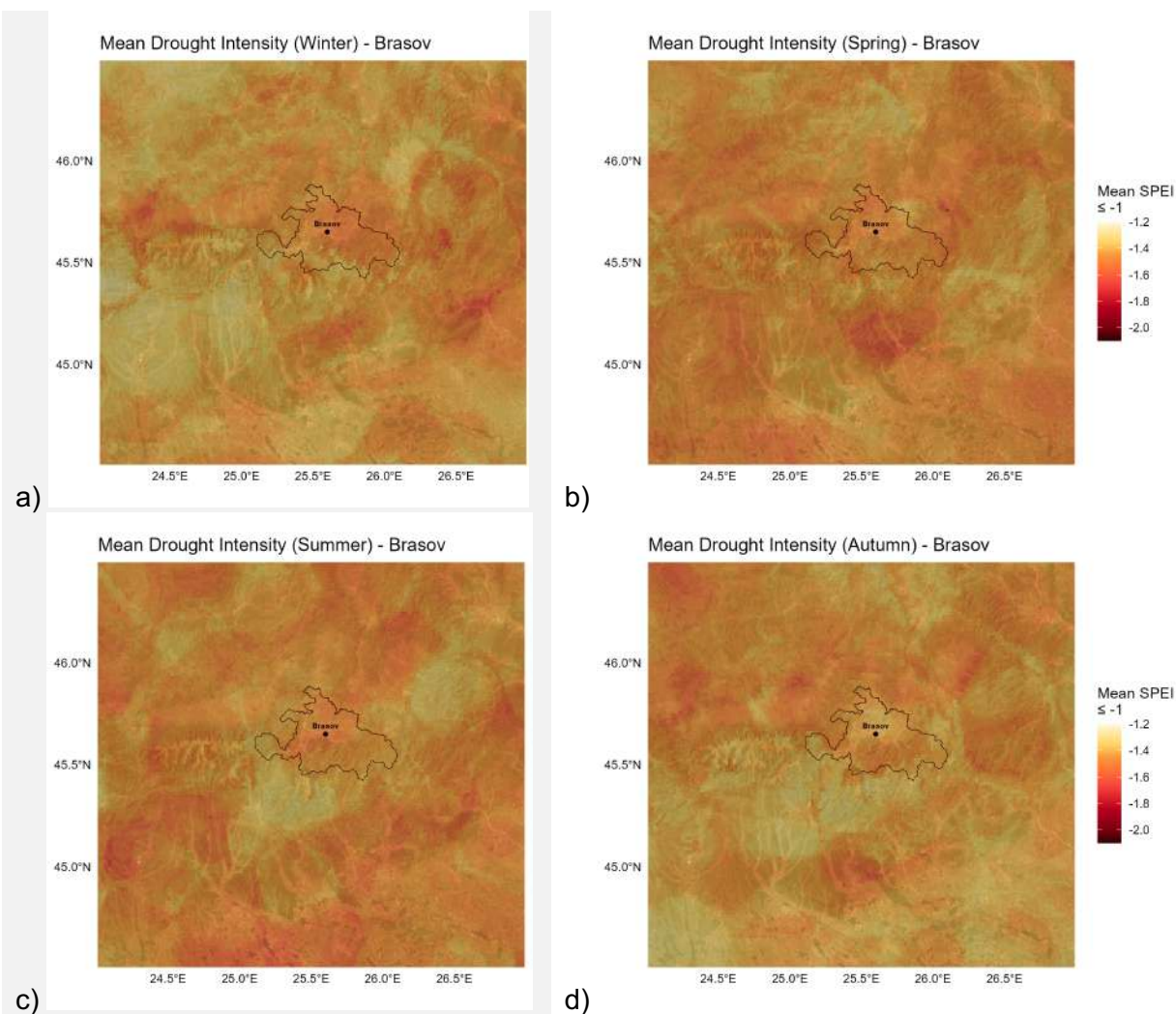


Figure A 2: Spatial distribution of seasonal drought intensity for the greater CSA Brasov area during 1990-2022 based on the SPEI-1 ≤ -1 (reference period 1992 - 2022), showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.1.3 CSA Prague

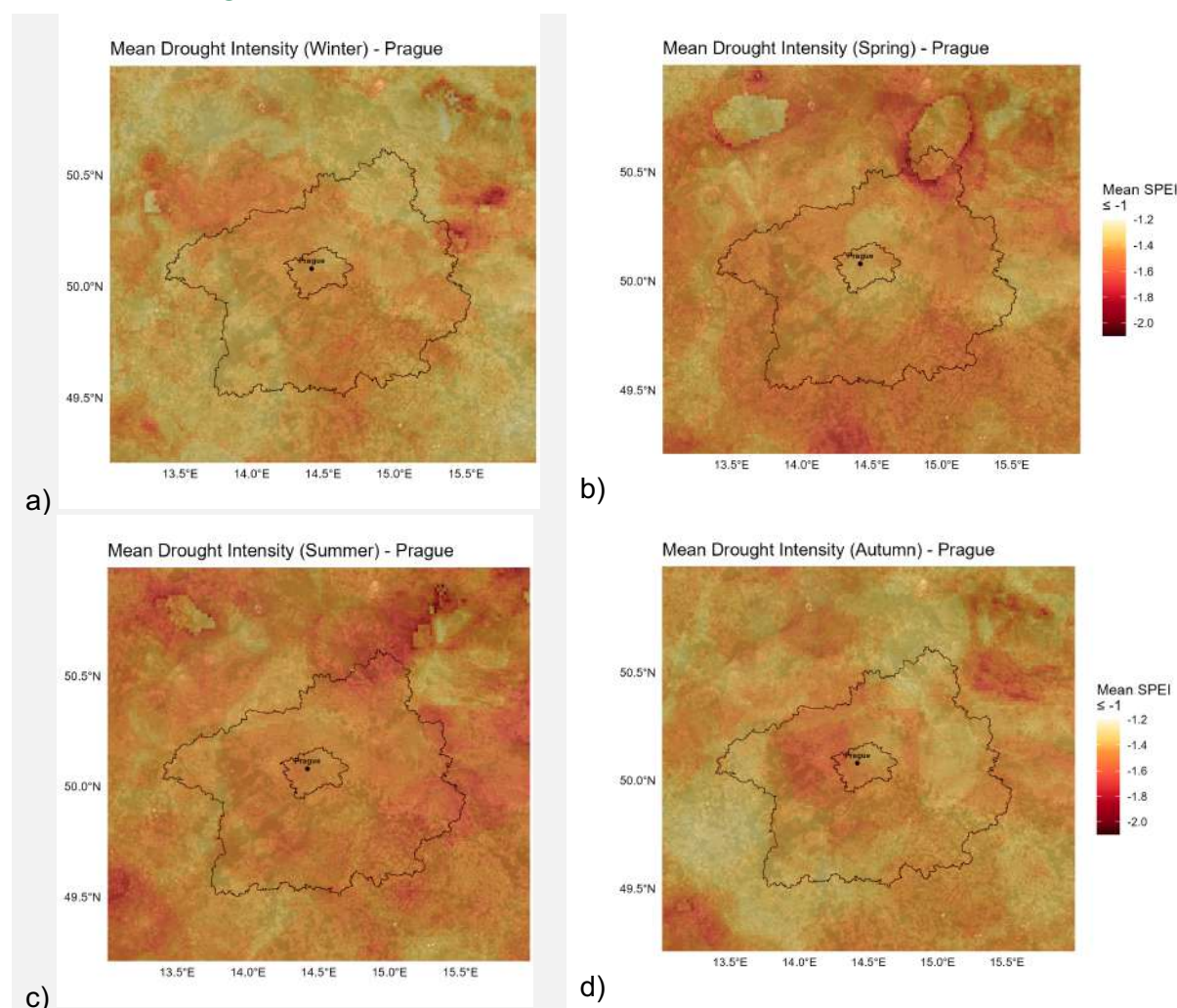


Figure A 3: Spatial distribution of seasonal drought intensity for the greater CSA Prague area during 1990-2022 based on the SPEI-1 ≤ -1 (reference period 1992 - 2022), showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.2 Seasonal Wetness Maps

The maps presented in this annex section illustrate the spatial distribution of key wetness characteristics, namely mean wetness intensity, calculated over the period 1990–2022 for each grid point within the respective CSAs and for each season. More details on the indicators used can be found at 3.2. Climate Indicators, while descriptions of the annual maps at 3.8. Floods, Extreme Precipitation, Wet Events.

9.2.1 CSA Leipzig

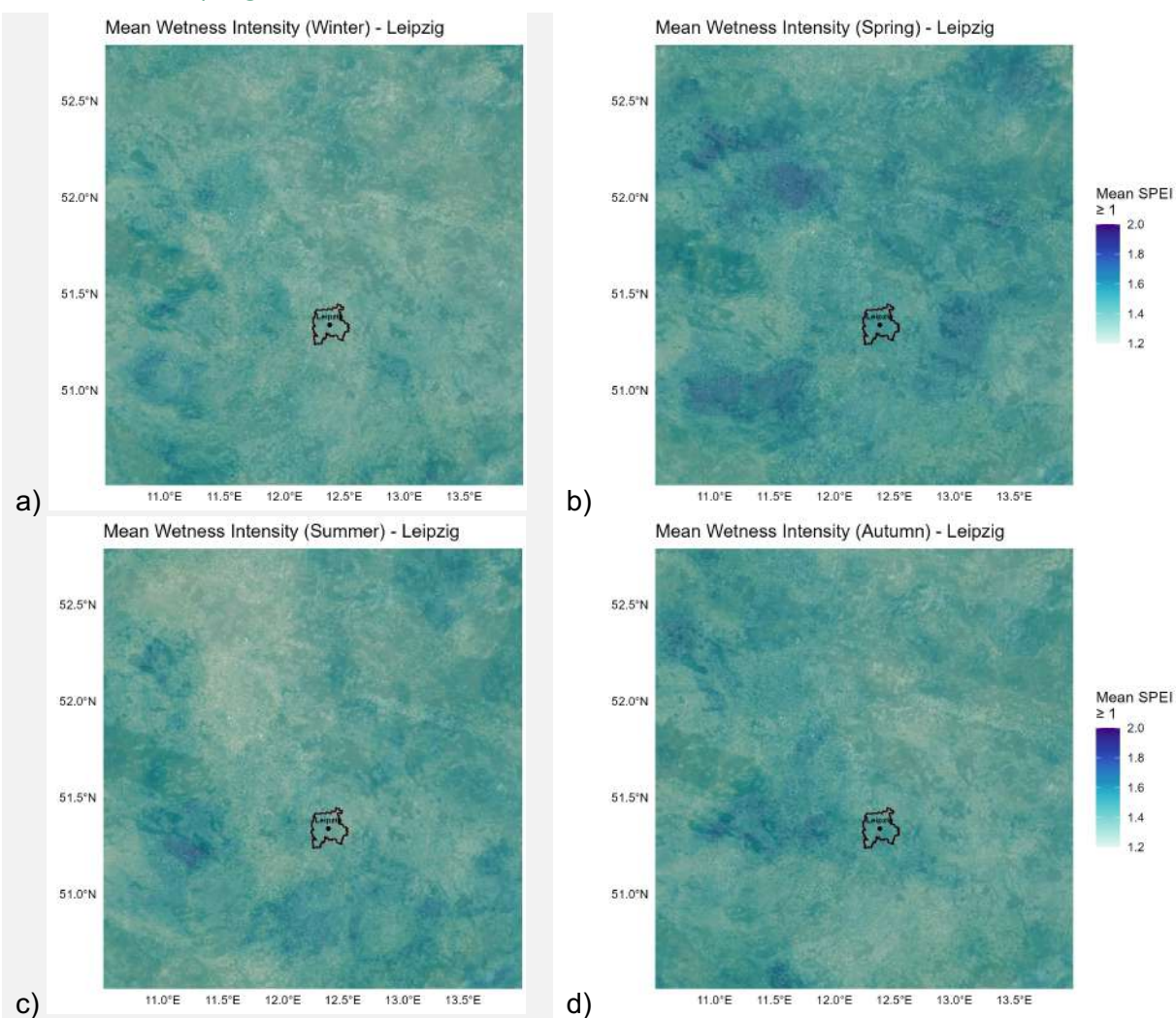


Figure A 4: Spatial distribution of seasonal wetness intensity for the greater CSA Leipzig area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022), showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.2.2 CSA Funen-Odense

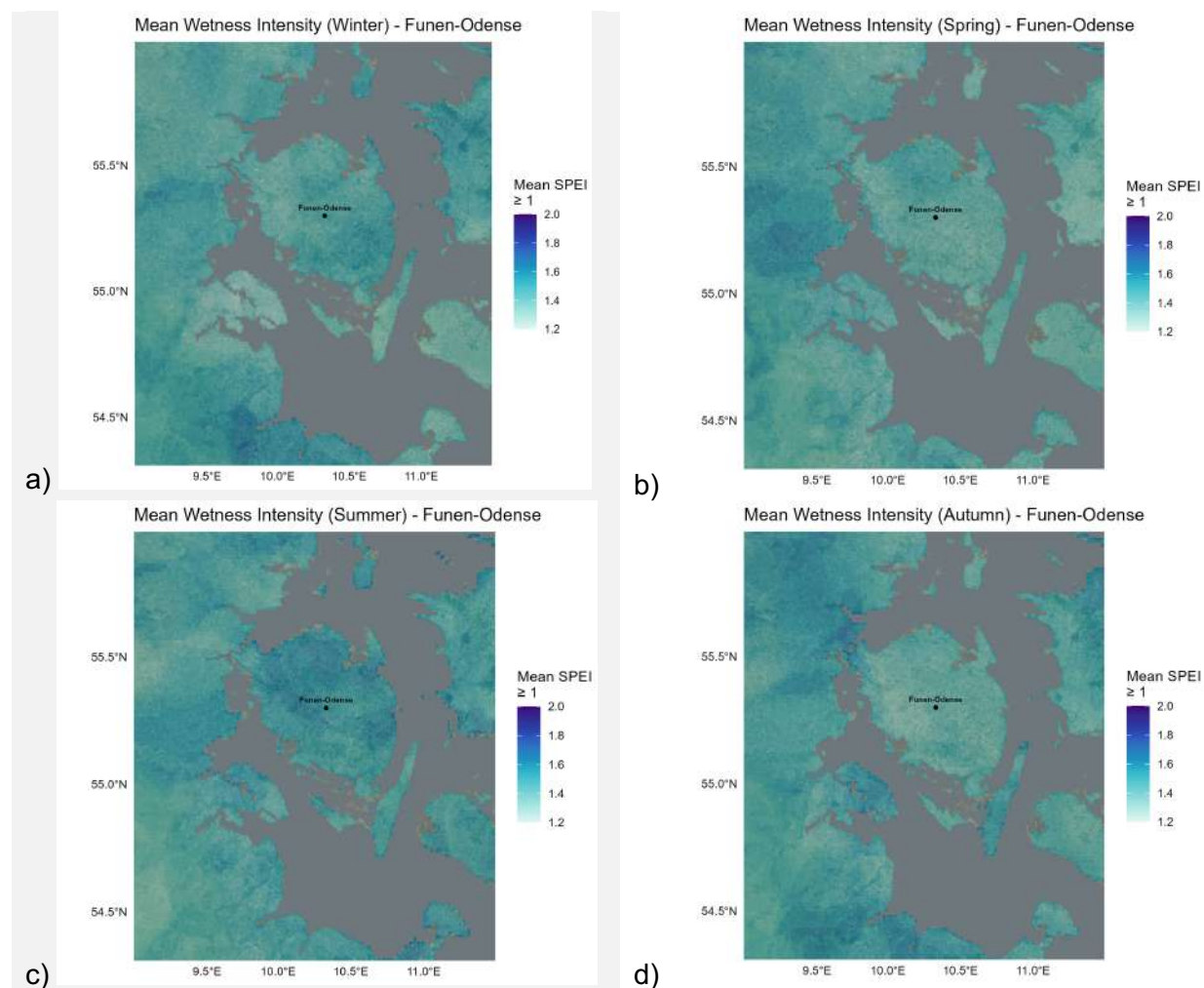


Figure A 5: Spatial distribution of seasonal wetness intensity for the greater CSA Funen-Odense area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022), showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.2.3 CSA Brasov

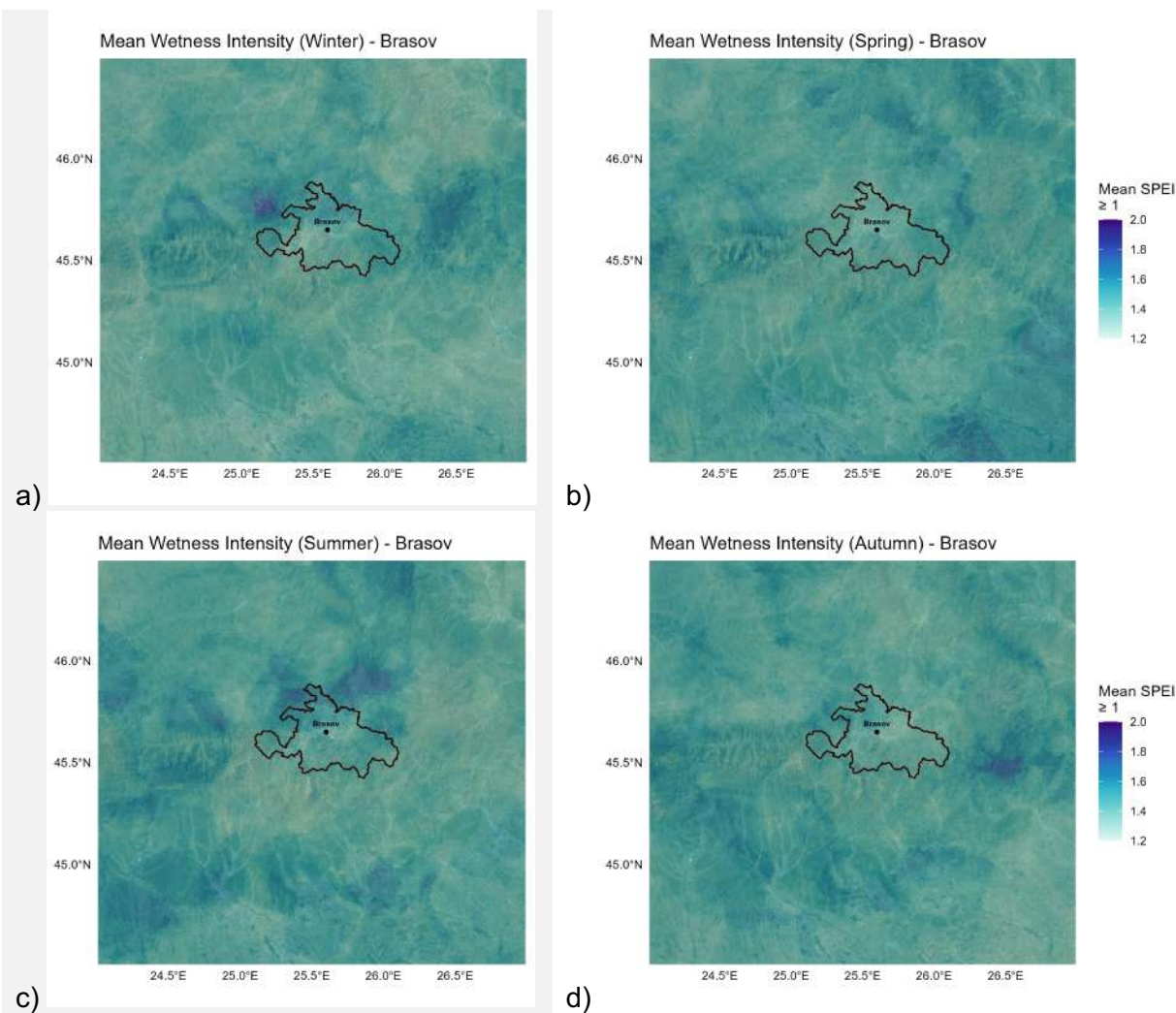


Figure A 6: Spatial distribution of seasonal wetness intensity for the greater CSA Brasov area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022), showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.2.4 CSA Birmingham

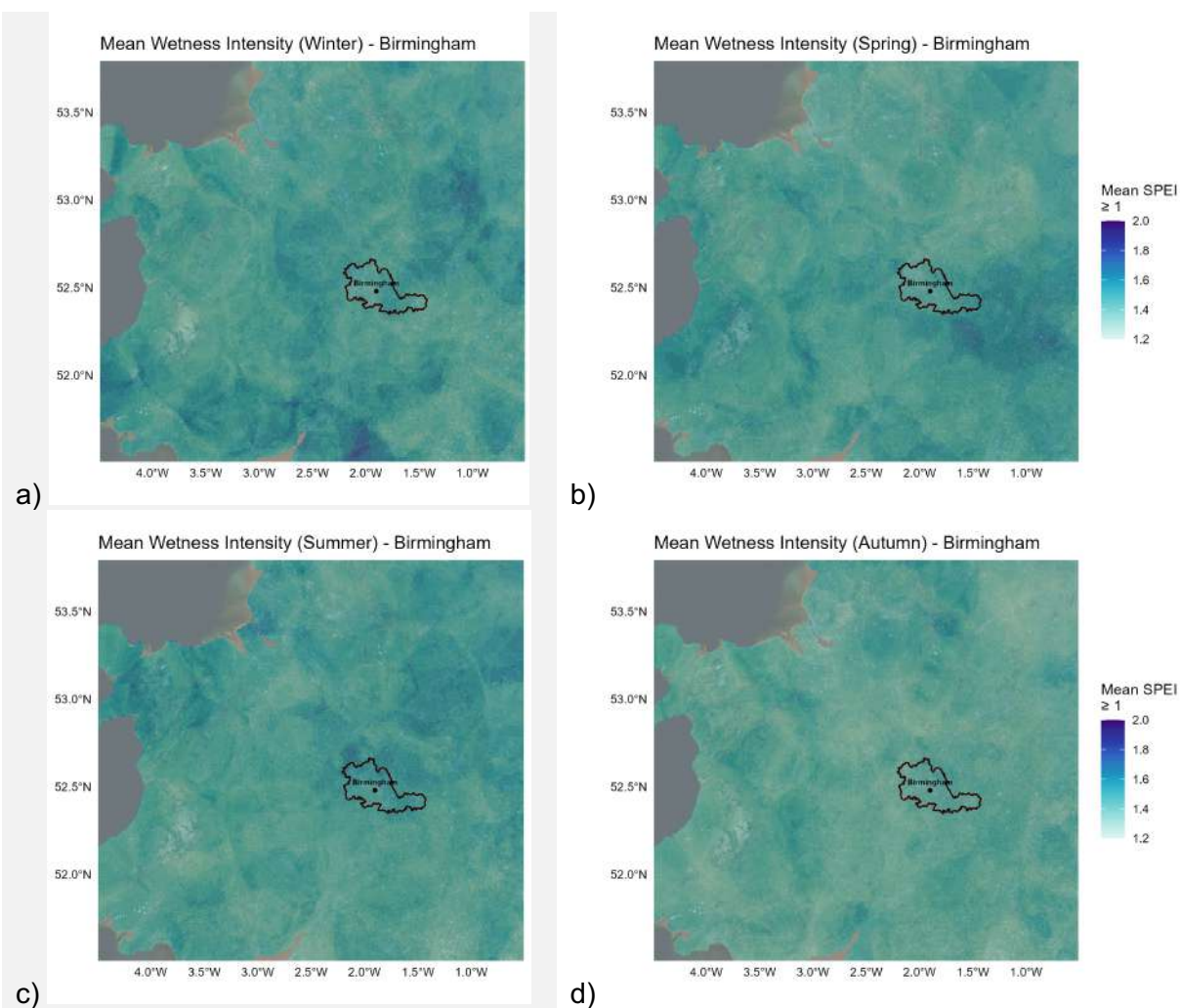


Figure A 7: Spatial distribution of seasonal wetness intensity for the greater CSA Birmingham area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022), showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.3 SPEI based on Modified Hargreaves

9.3.1 Drought Characteristics

9.3.1.1 Barcelona

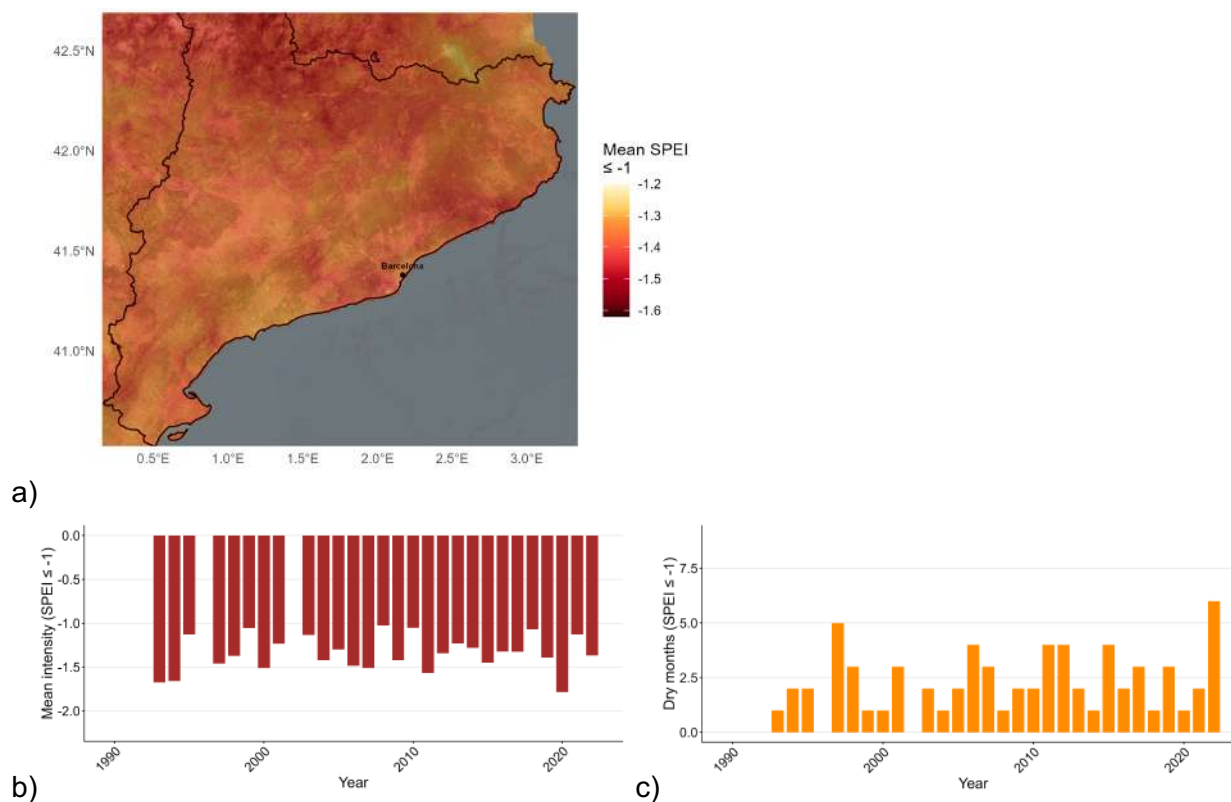
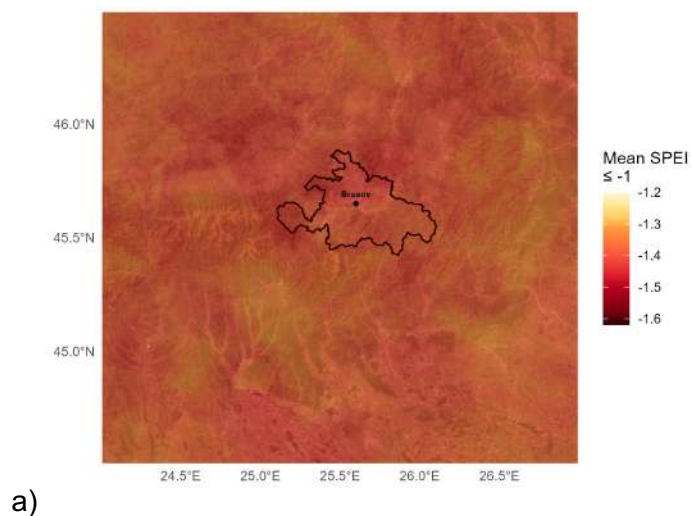


Figure A 8: Drought characteristics for the greater CSA Barcelona area based on the SPEI-1 ≤ -1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.3.1.2 Brasov



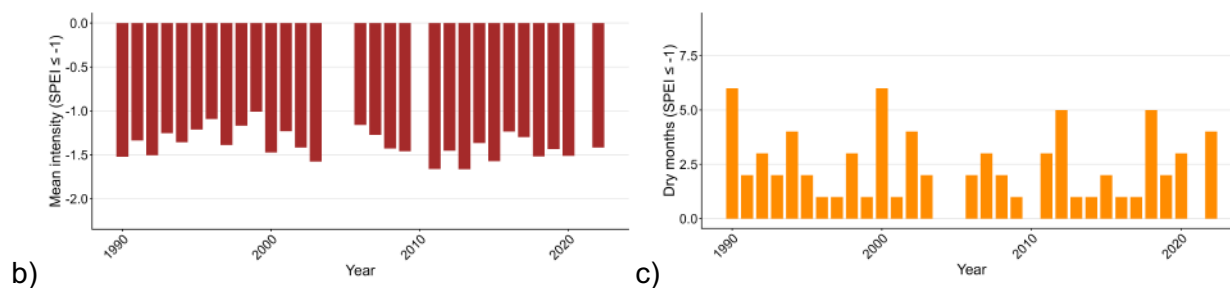


Figure A 9: Drought characteristics for the greater CSA Brasov area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.3.1.3 Prague

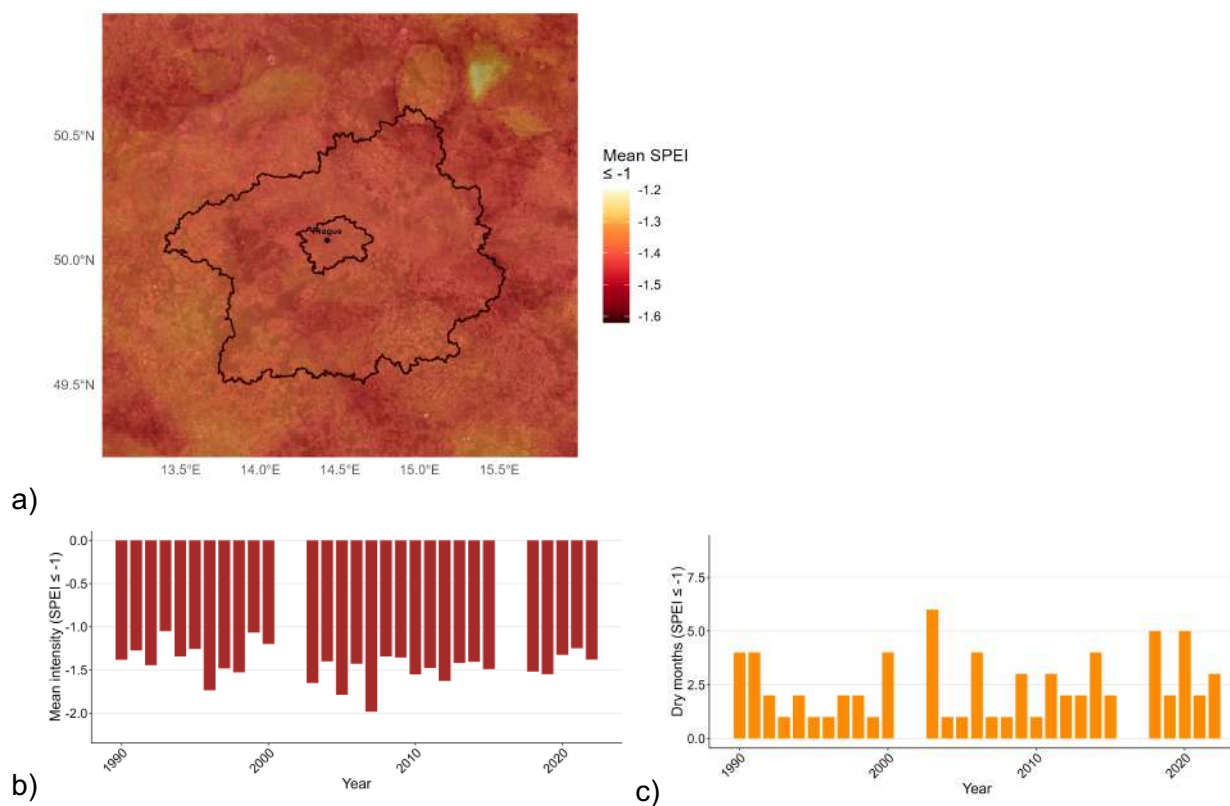


Figure A 10: Drought characteristics for the greater CSA Prague area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.3.2 Wetness Characteristics

9.3.2.1 Leipzig

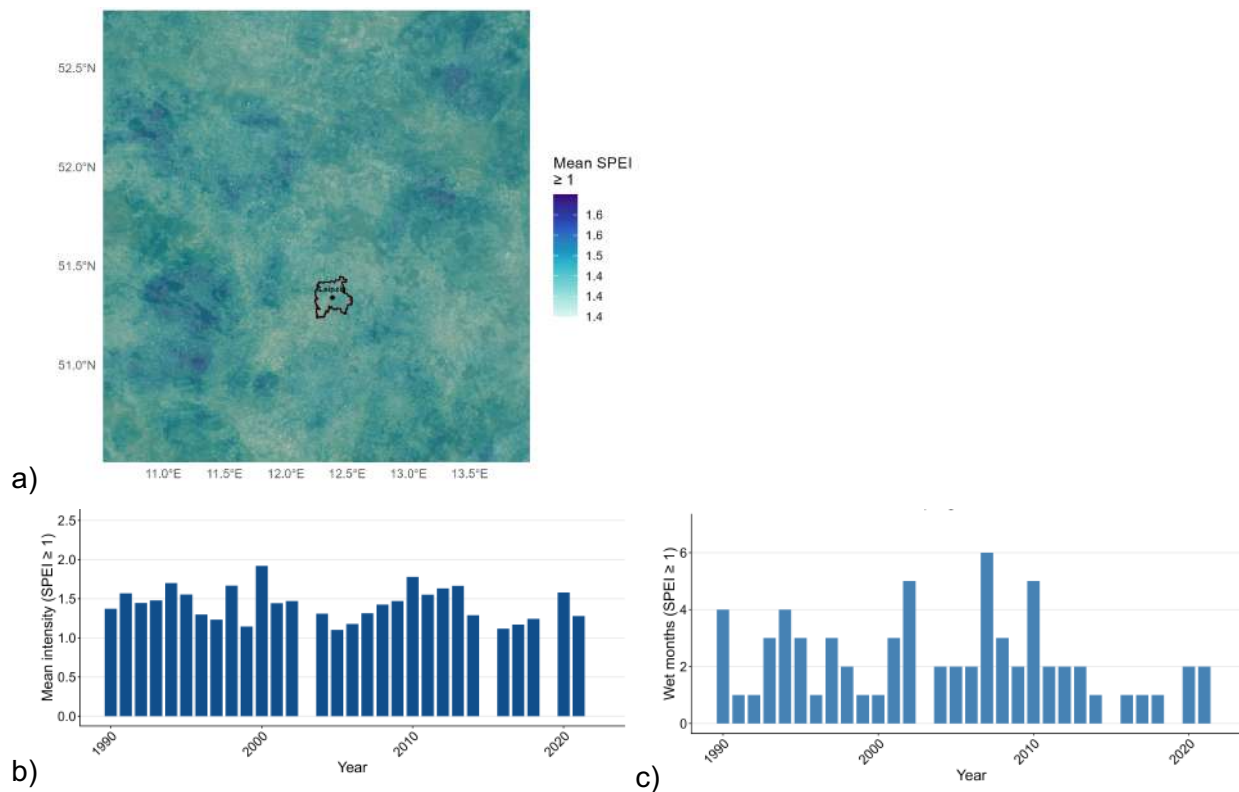
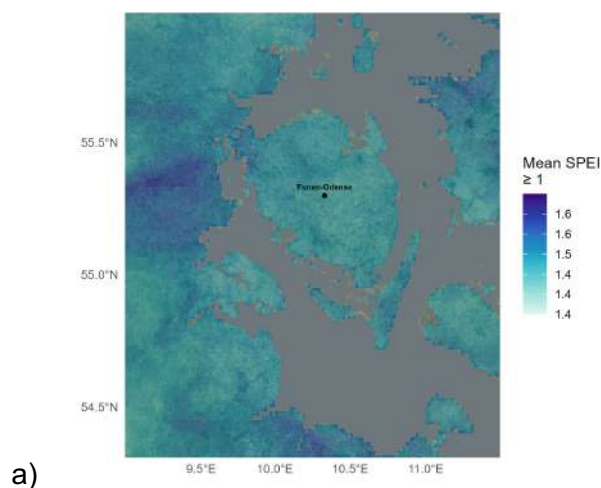


Figure A 11: Wetness characteristics for the greater CSA Leipzig area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.3.2.2 Funen-Odense



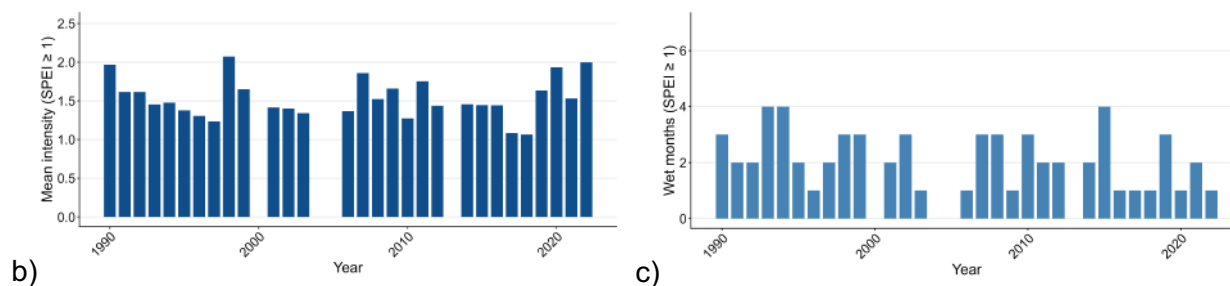


Figure A 12: Wetness characteristics for the greater CSA Funen-Odense area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.3.2.3 Brasov

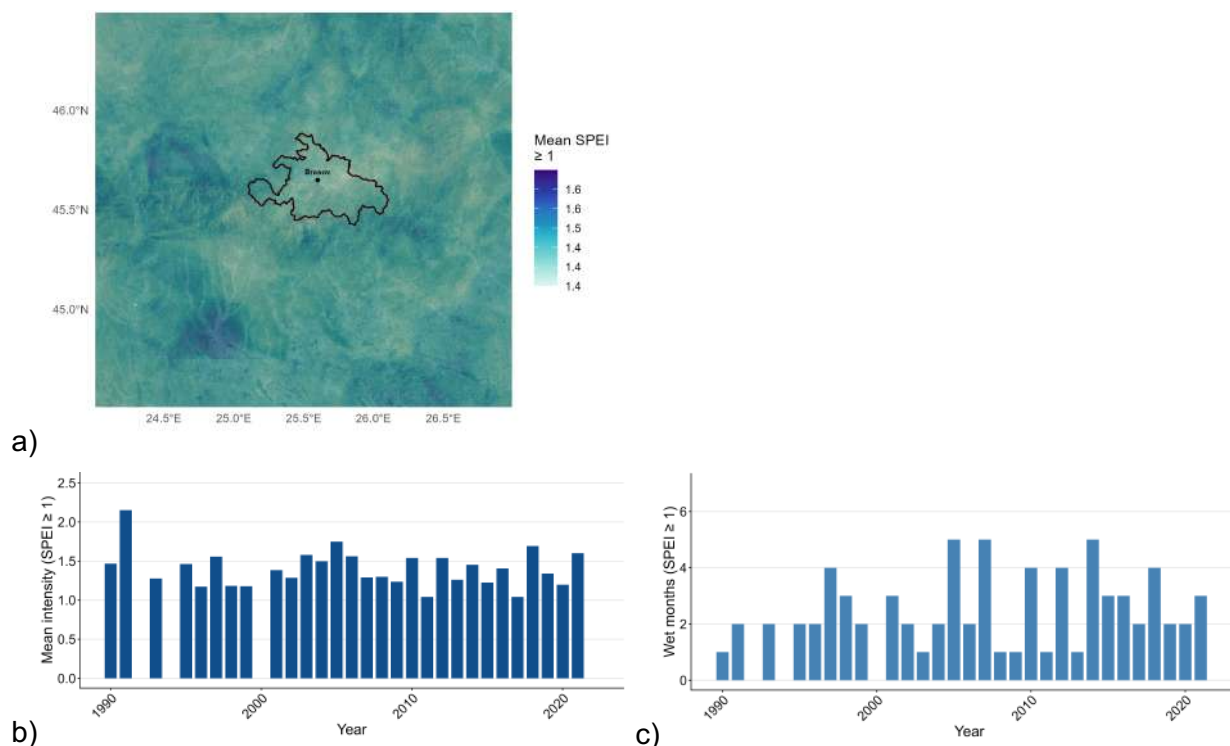


Figure A 13: Wetness characteristics for the greater CSA Brasov area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.3.2.4 Birmingham

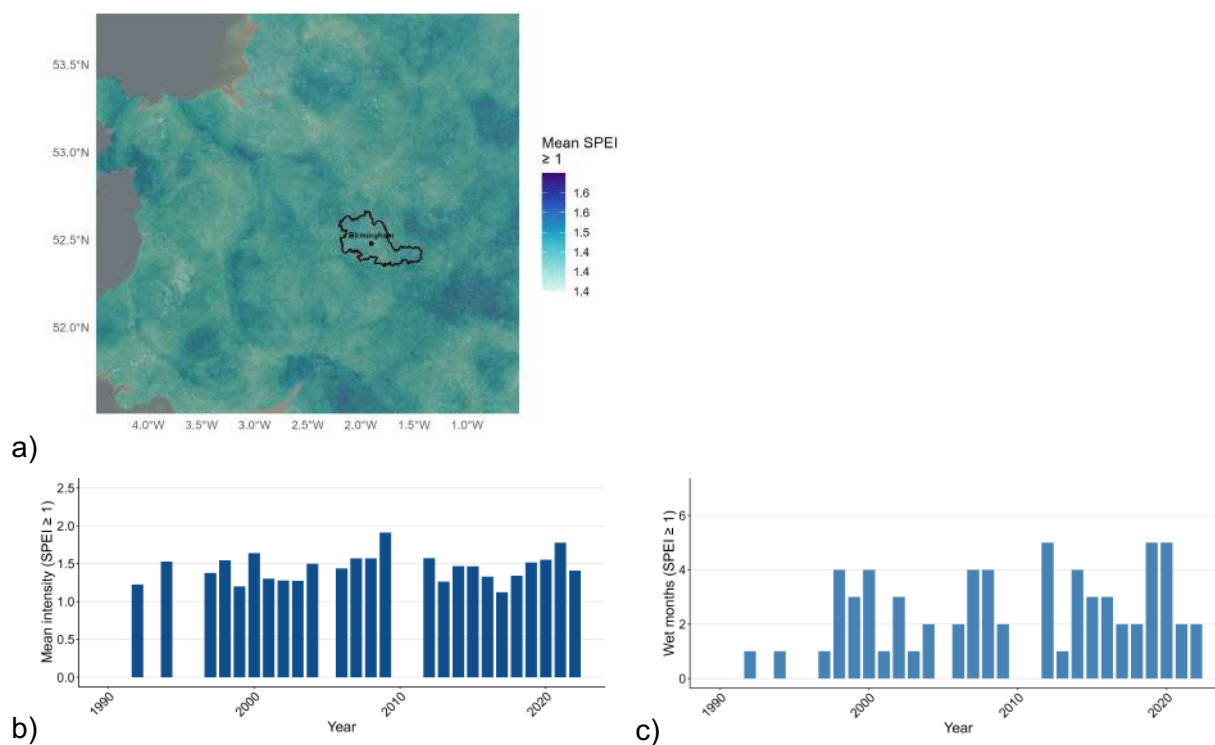
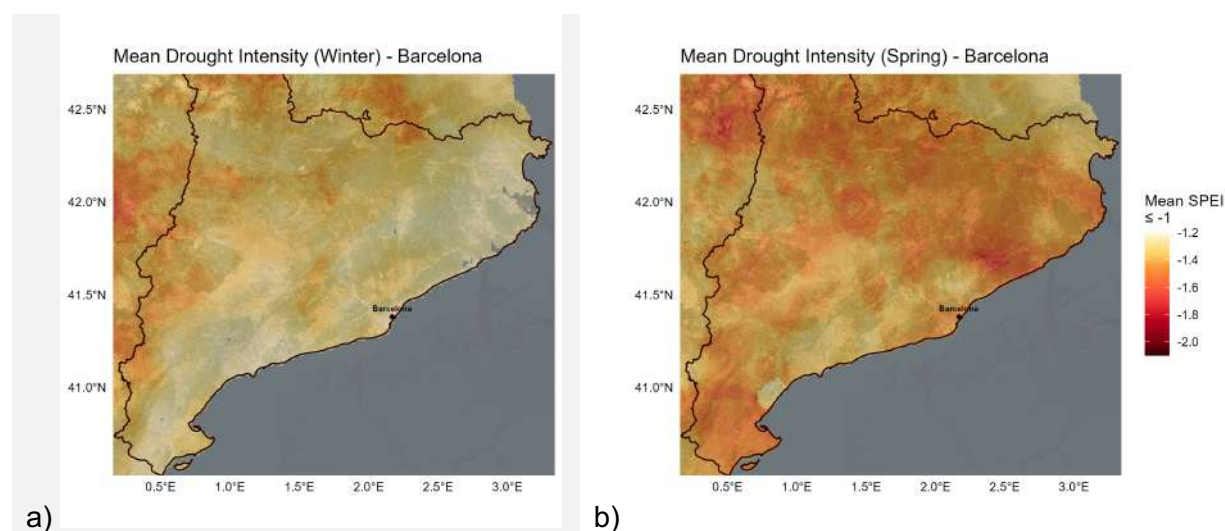


Figure A 14: Wetness characteristics for the greater CSA Birmingham area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.3.3 Seasonal Drought Maps

9.3.3.1 Barcelona



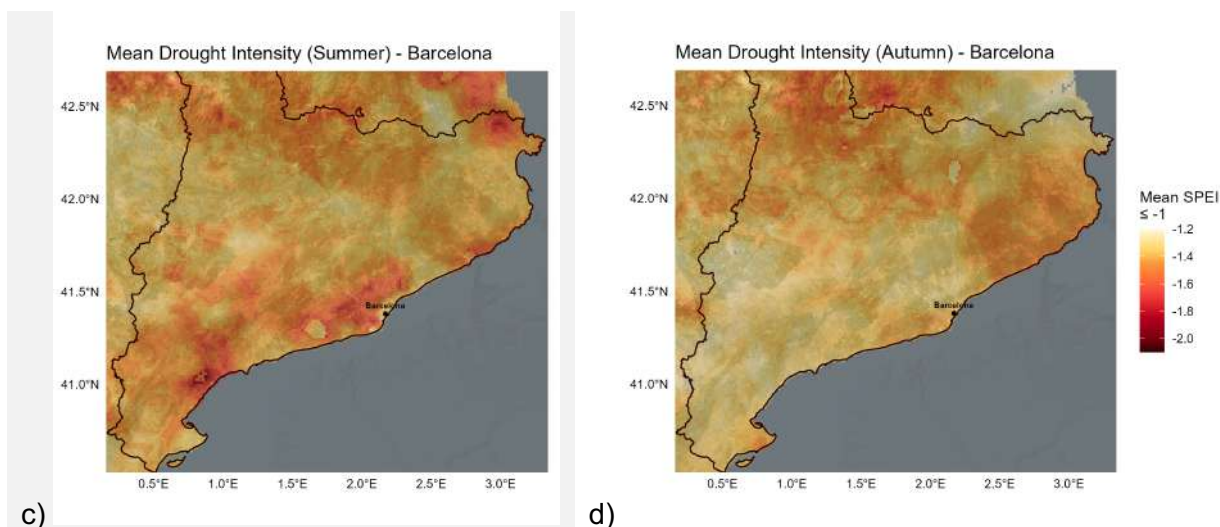
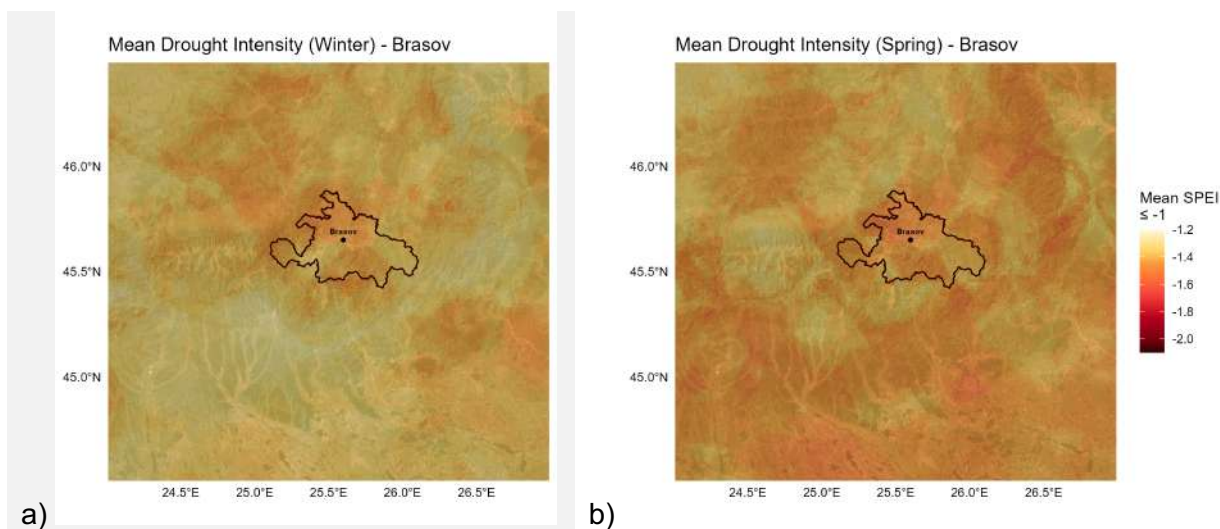


Figure A 15: Spatial distribution of seasonal drought intensity for the greater CSA Barcelona area during 1990-2022 based on the $SPEI-1 \leq 1$ (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.3.3.2 Brasov



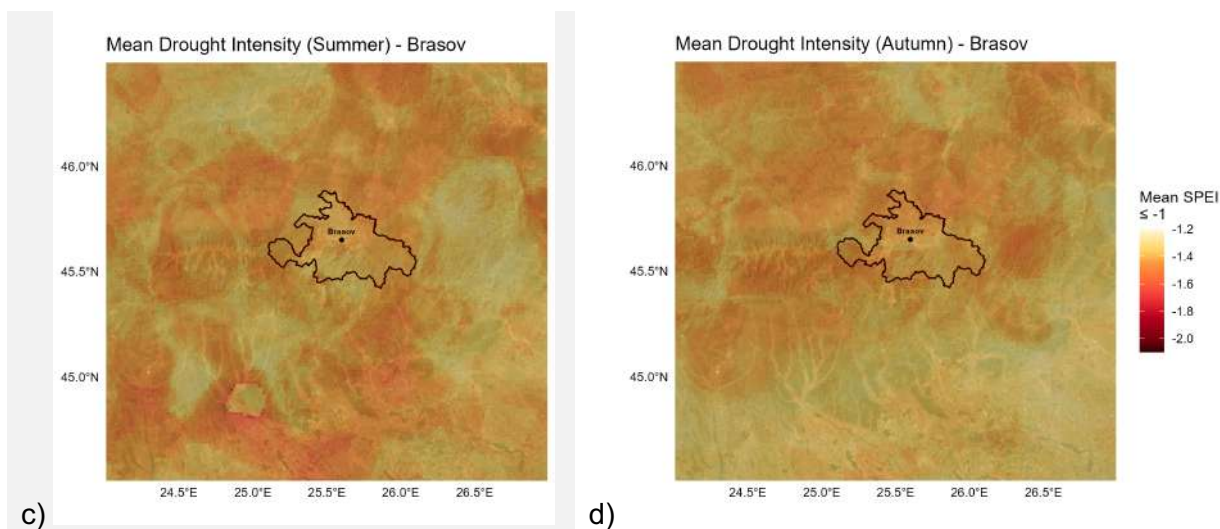
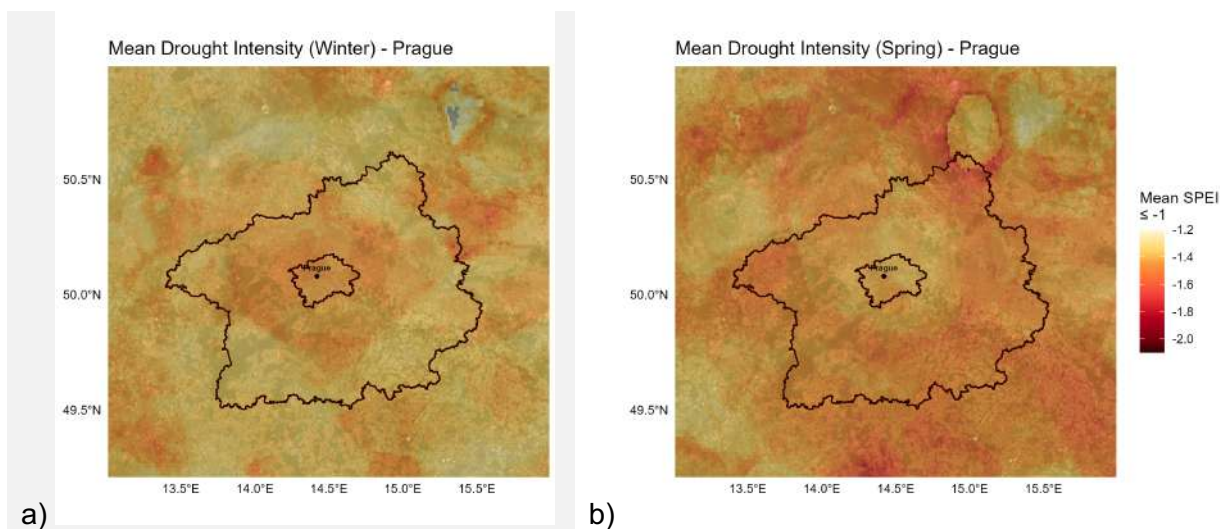


Figure A 16: Spatial distribution of seasonal drought intensity for the greater CSA Barcelona area during 1990-2022 based on the $SPEI-1 \leq 1$ (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.3.3.3 Prague



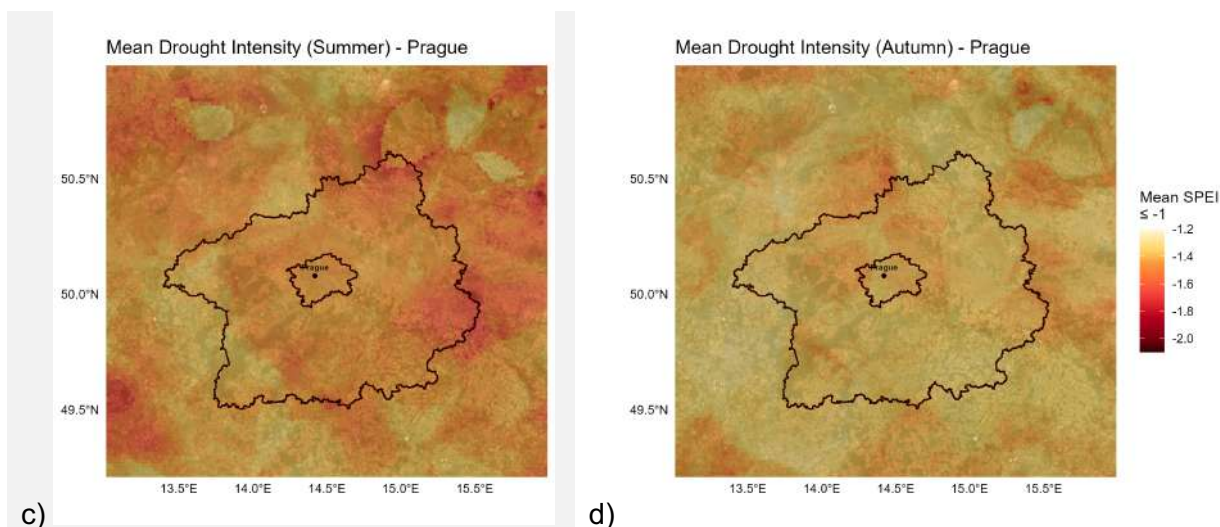
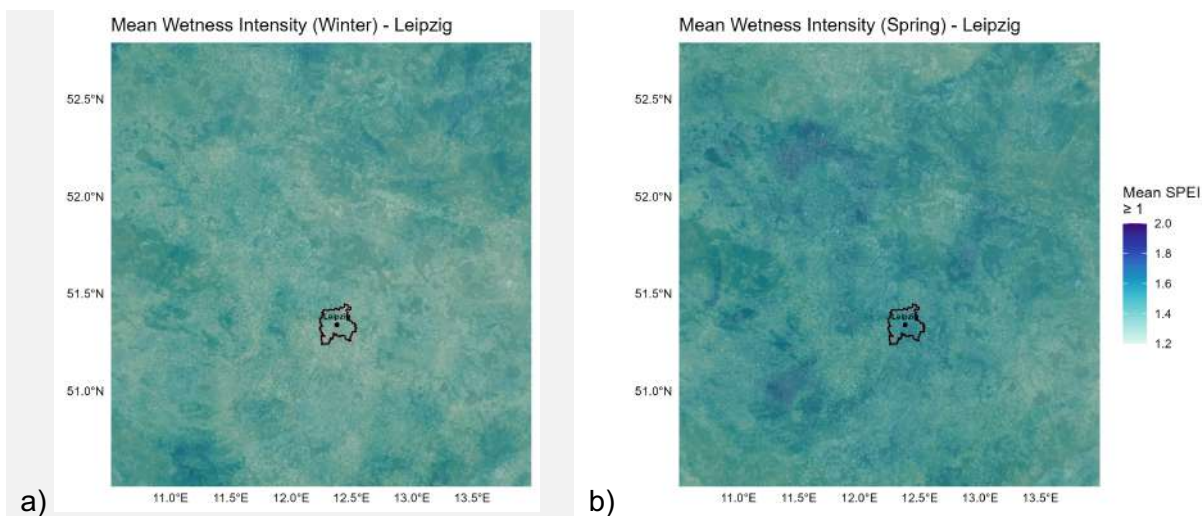


Figure A 17: Spatial distribution of seasonal drought intensity for the greater CSA Prague area during 1990-2022 based on the $SPEI-1 \leq 1$ (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.3.4 Seasonal Wetness Maps

9.3.4.1 Leipzig



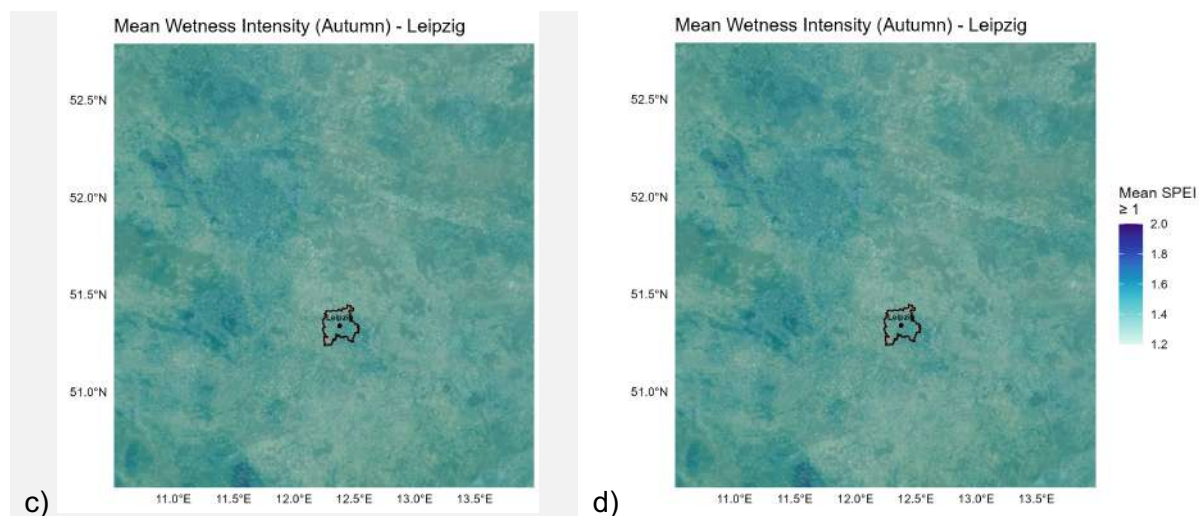
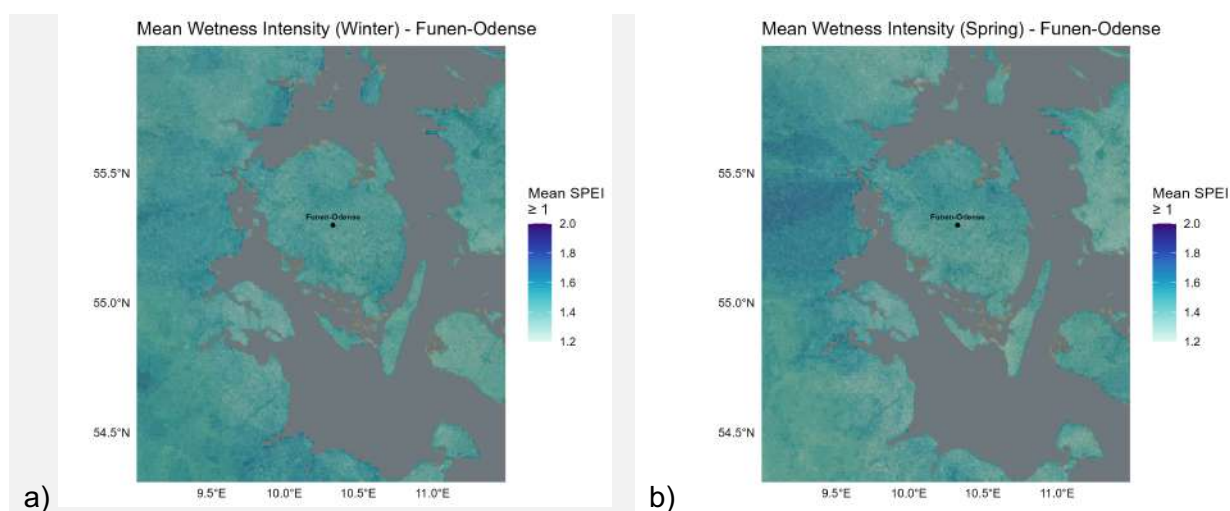


Figure A 18: Spatial distribution of seasonal wetness intensity for the greater CSA Birmingham area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.3.4.2 Funen-Odense



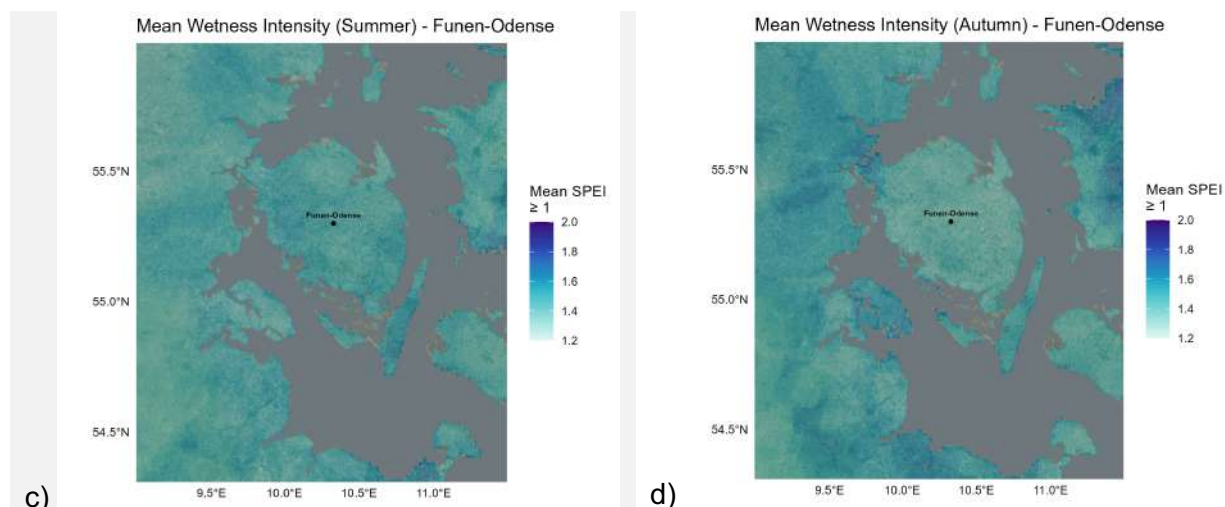
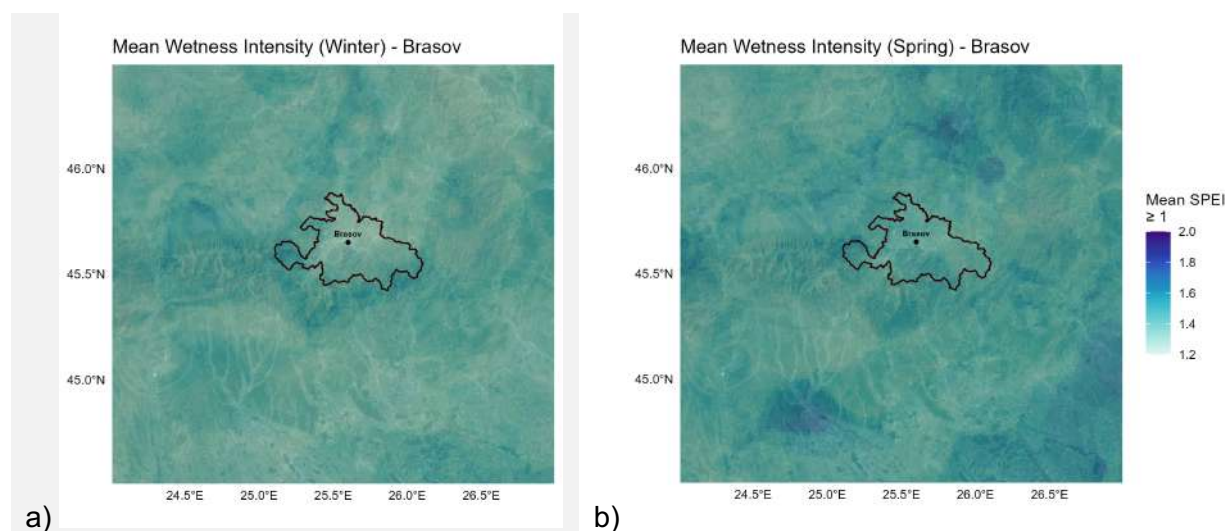


Figure A 19: Spatial distribution of seasonal wetness intensity for the greater CSA Funen-Odense area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.3.4.3 Brasov



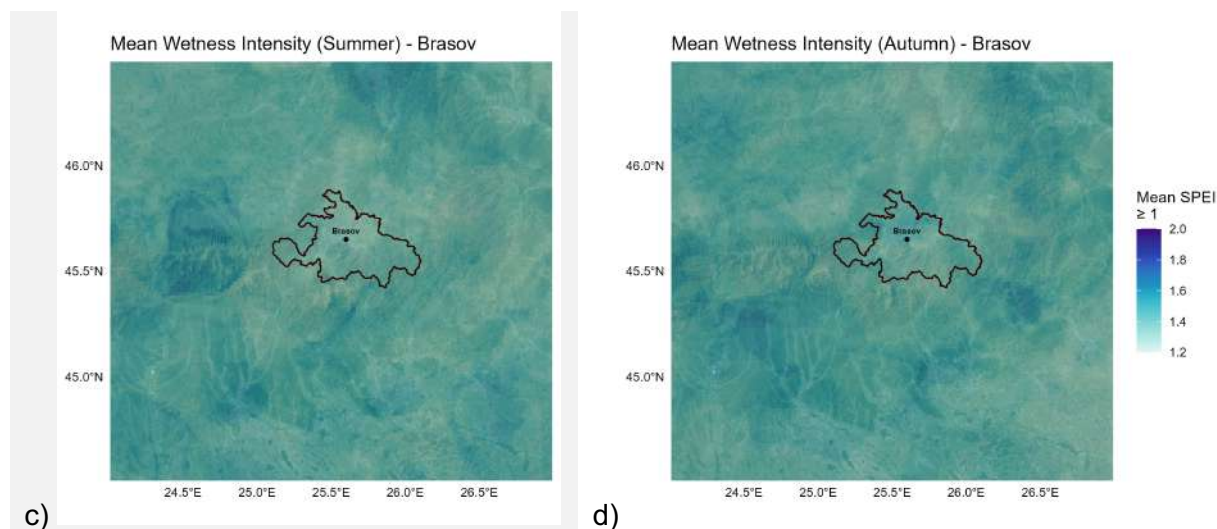
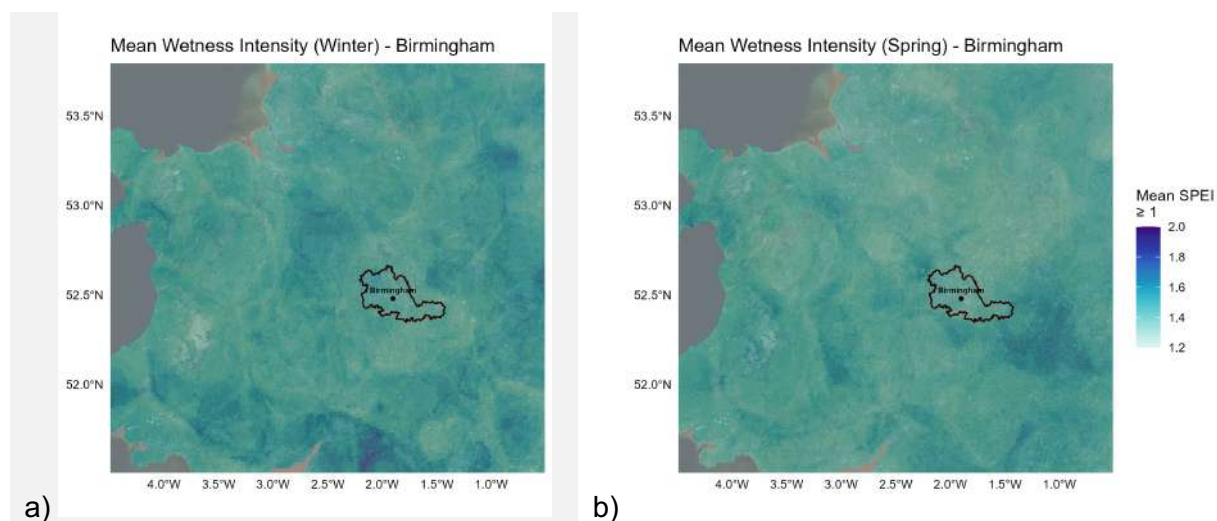


Figure A 20: Spatial distribution of seasonal wetness intensity for the greater CSA Brasov area during 1990-2022 based on the $SPEI-1 \geq 1$ (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.3.4.4 Birmingham



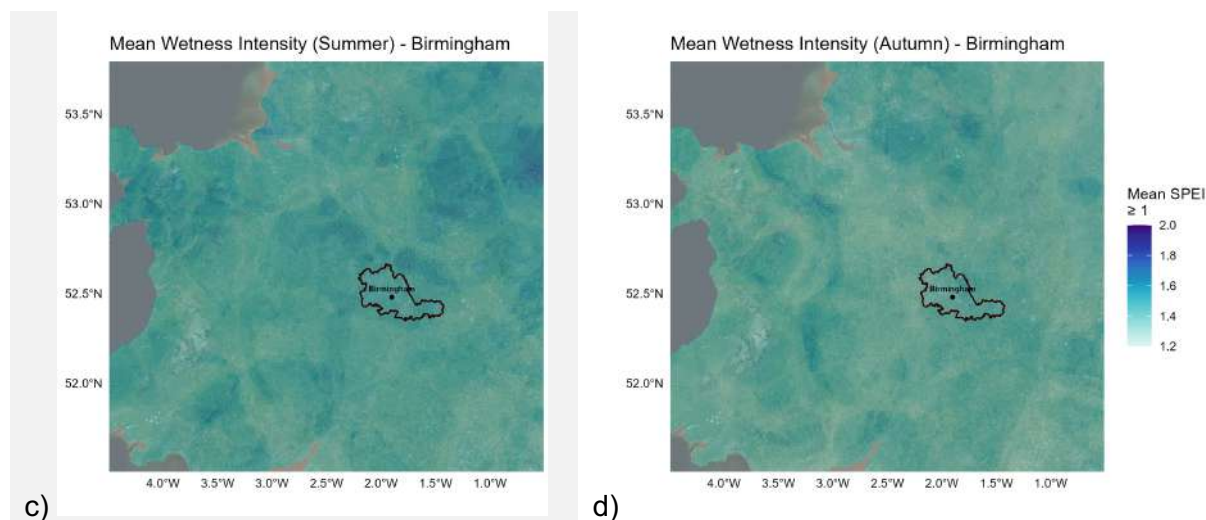


Figure A 21: Spatial distribution of seasonal wetness intensity for the greater CSA Birmingham area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.4 SPEI based on Modified Hargreaves and E-OBS Data

9.4.1 Drought Characteristics

9.4.1.1 Barcelona

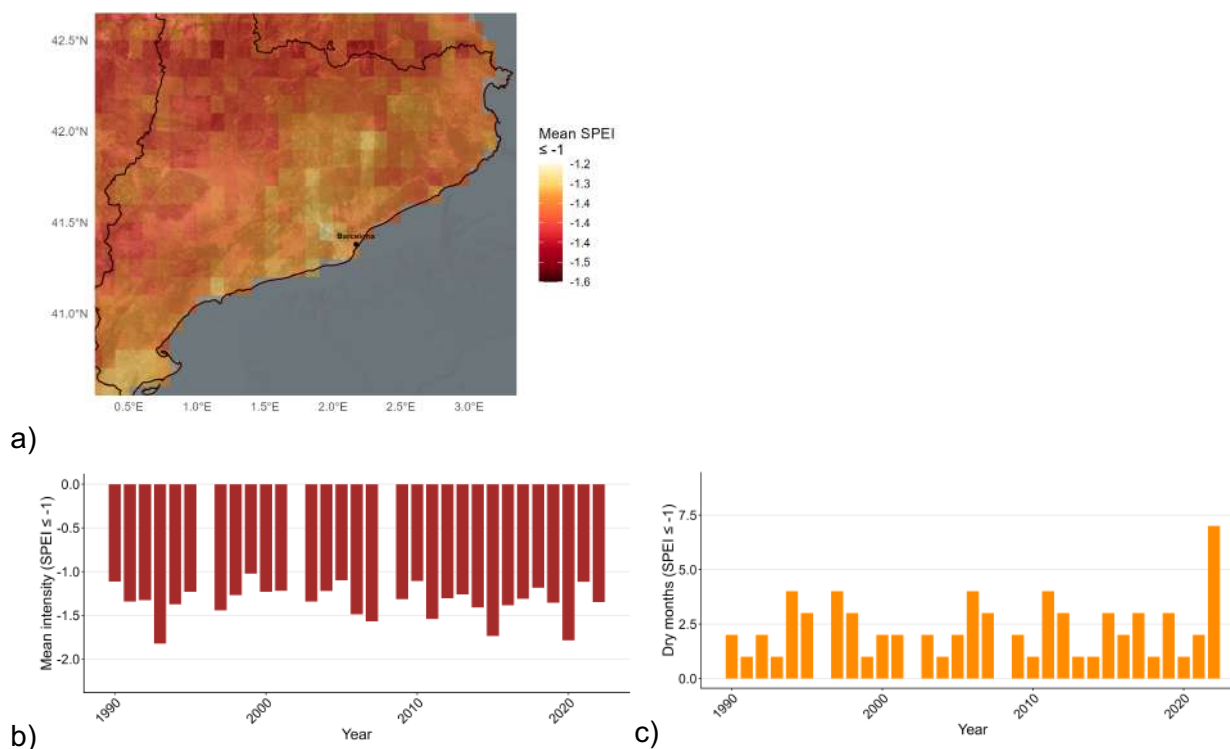


Figure A 22: Drought characteristics for the greater CSA Barcelona area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.4.1.2 Brasov

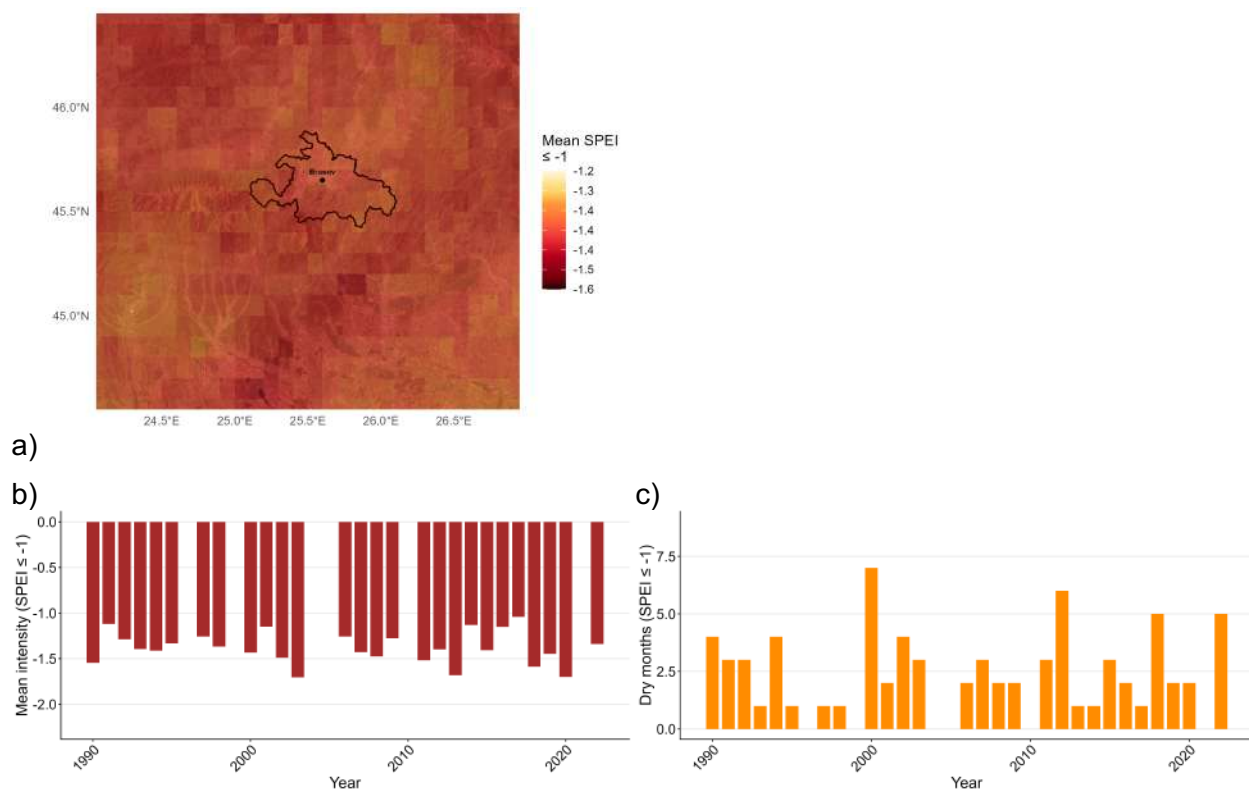
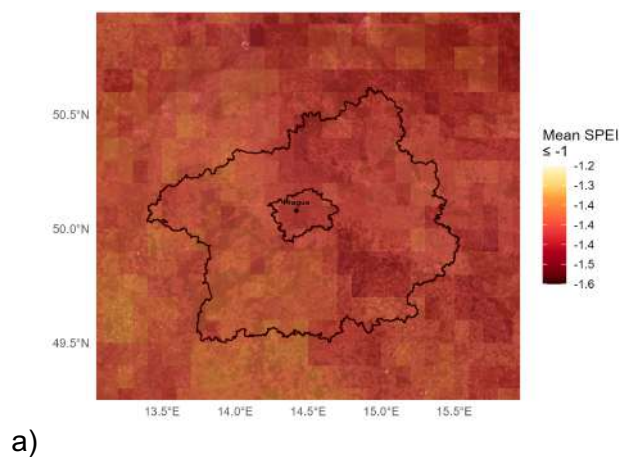


Figure A 23: Drought characteristics for the greater CSA Brasov area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.4.1.3 Prague



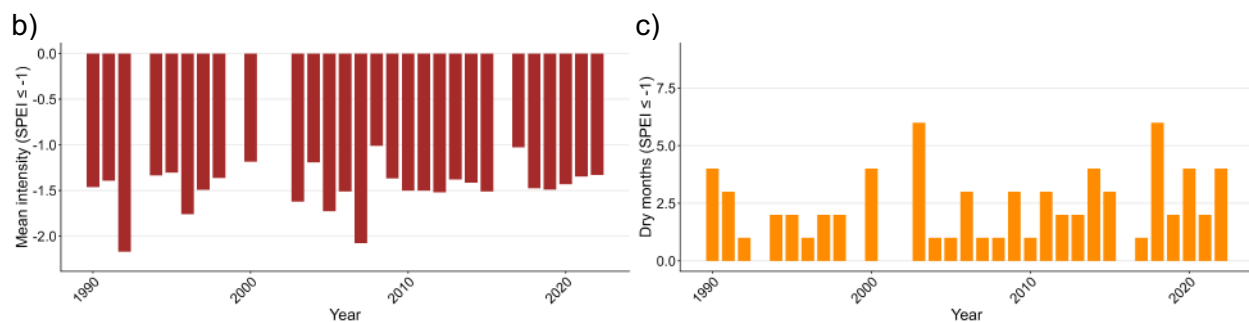


Figure A 24: Drought characteristics for the greater CSA Prague area based on the $SPEI-1 \leq -1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.4.2 Wetness Characteristics

9.4.2.1 Leipzig

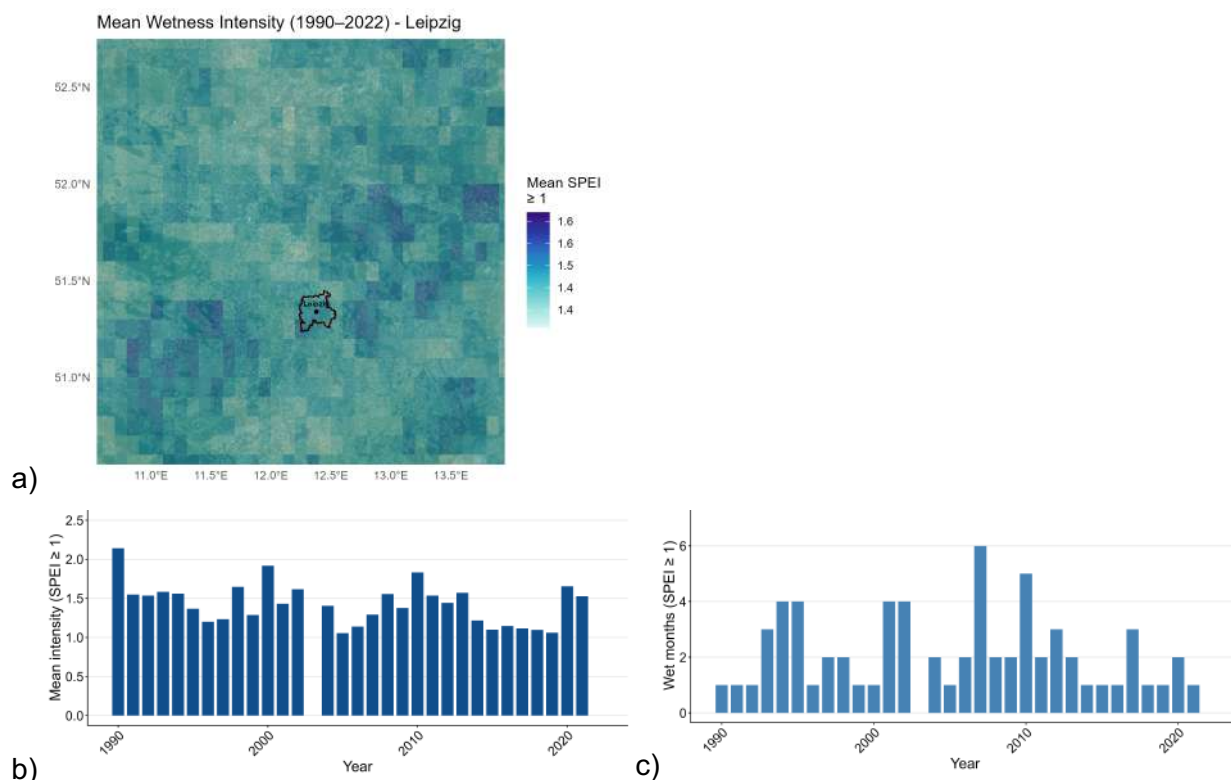


Figure A 25: Wetness characteristics for the greater CSA Leipzig area based on the $SPEI-1 \geq 1$ (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.4.2.2 Funen-Odense

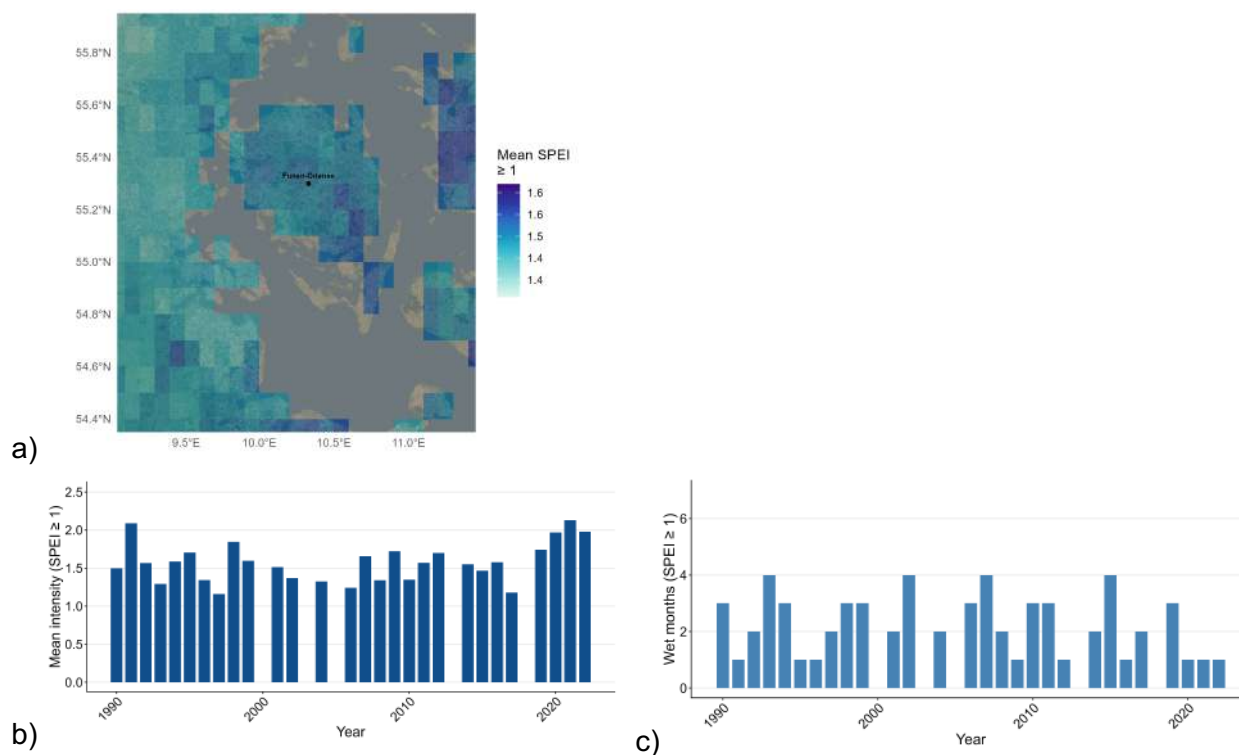
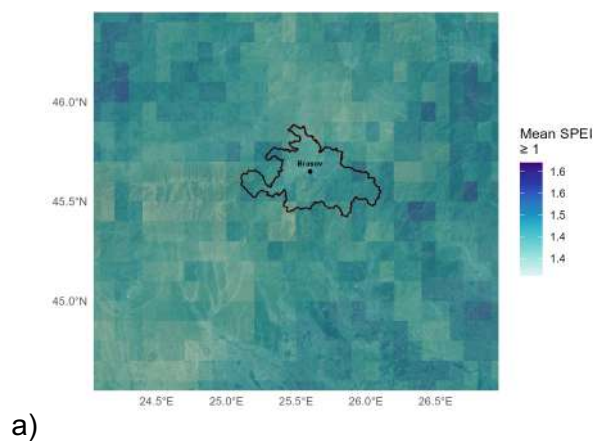


Figure A 26: Wetness characteristics for the greater CSA Funen-Odense area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.4.2.3 Brasov



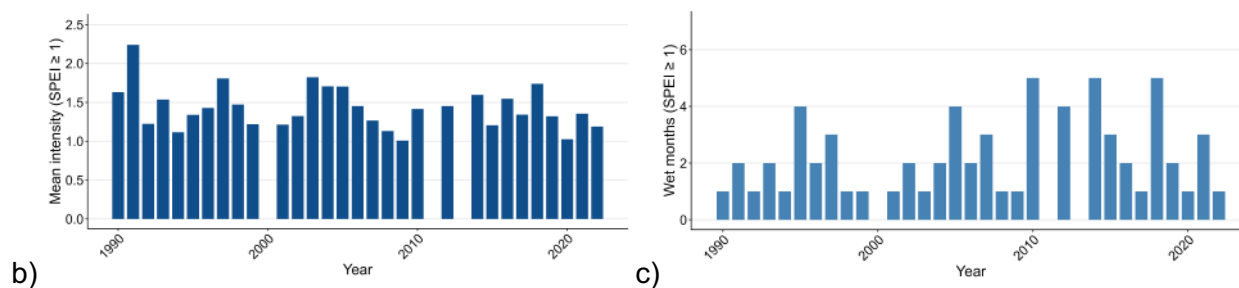


Figure A 27: Wetness characteristics for the greater CSA Brasov area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.4.2.4 Birmingham

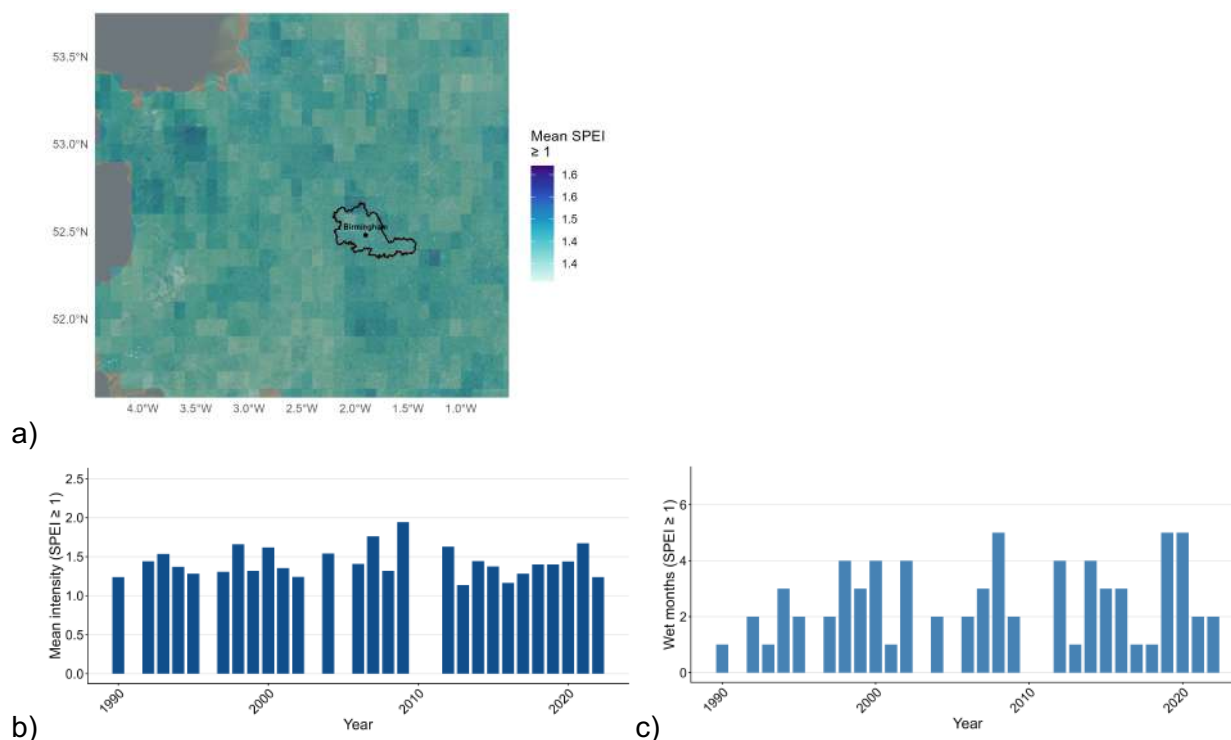


Figure A 28: Wetness characteristics for the greater CSA Birmingham area based on the SPEI-1 ≥ 1 (reference period 1992–2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) mean wetness intensity, (b) mean annual wetness intensity and (c) number of wet months per year, during 1990–2022.

9.4.3 Seasonal Drought Maps

9.4.3.1 Barcelona

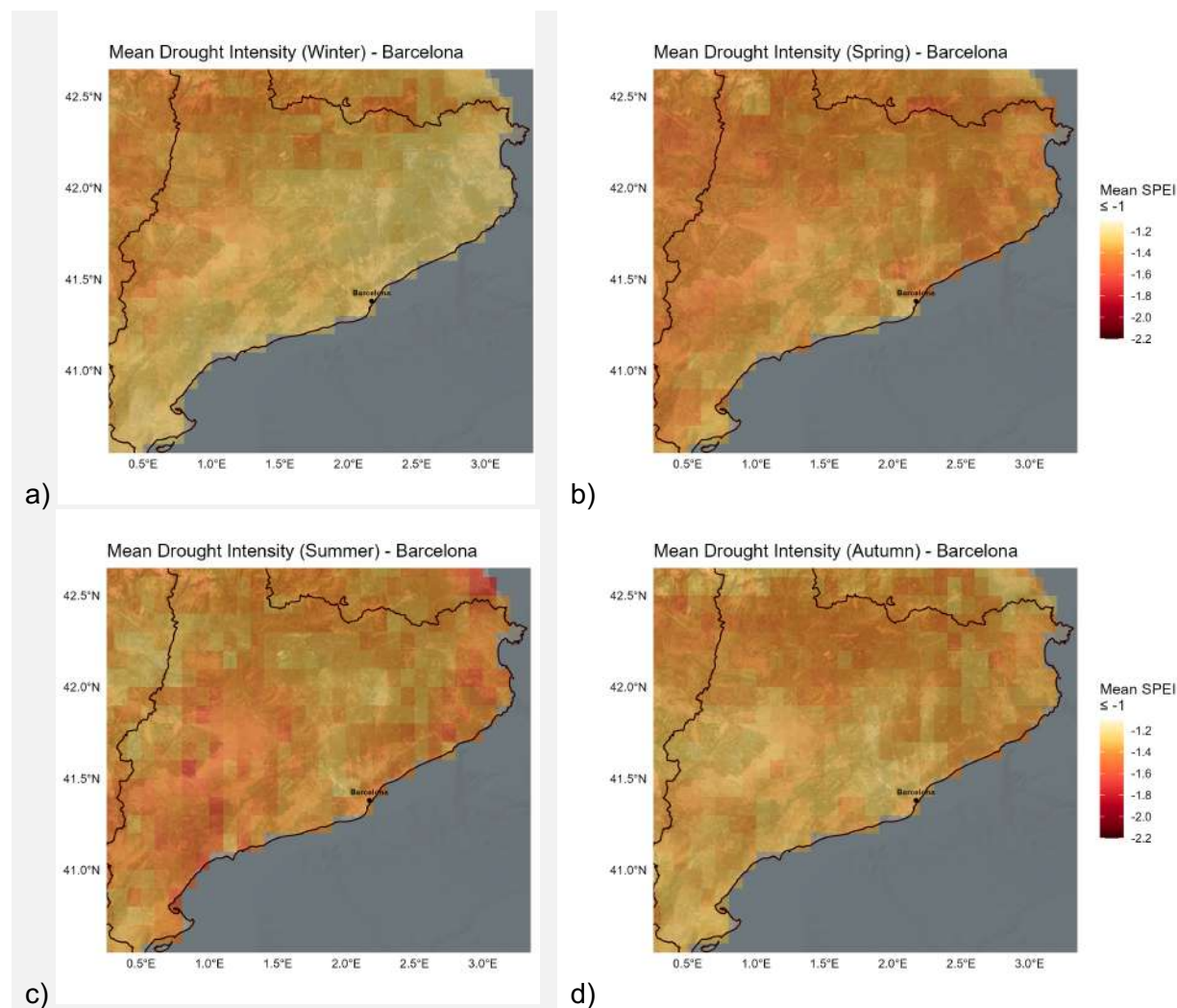


Figure A 29: Spatial distribution of seasonal drought intensity for the greater CSA Barcelona area during 1990-2022 based on the SPEI-1 ≤ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.4.3.2 Brasov

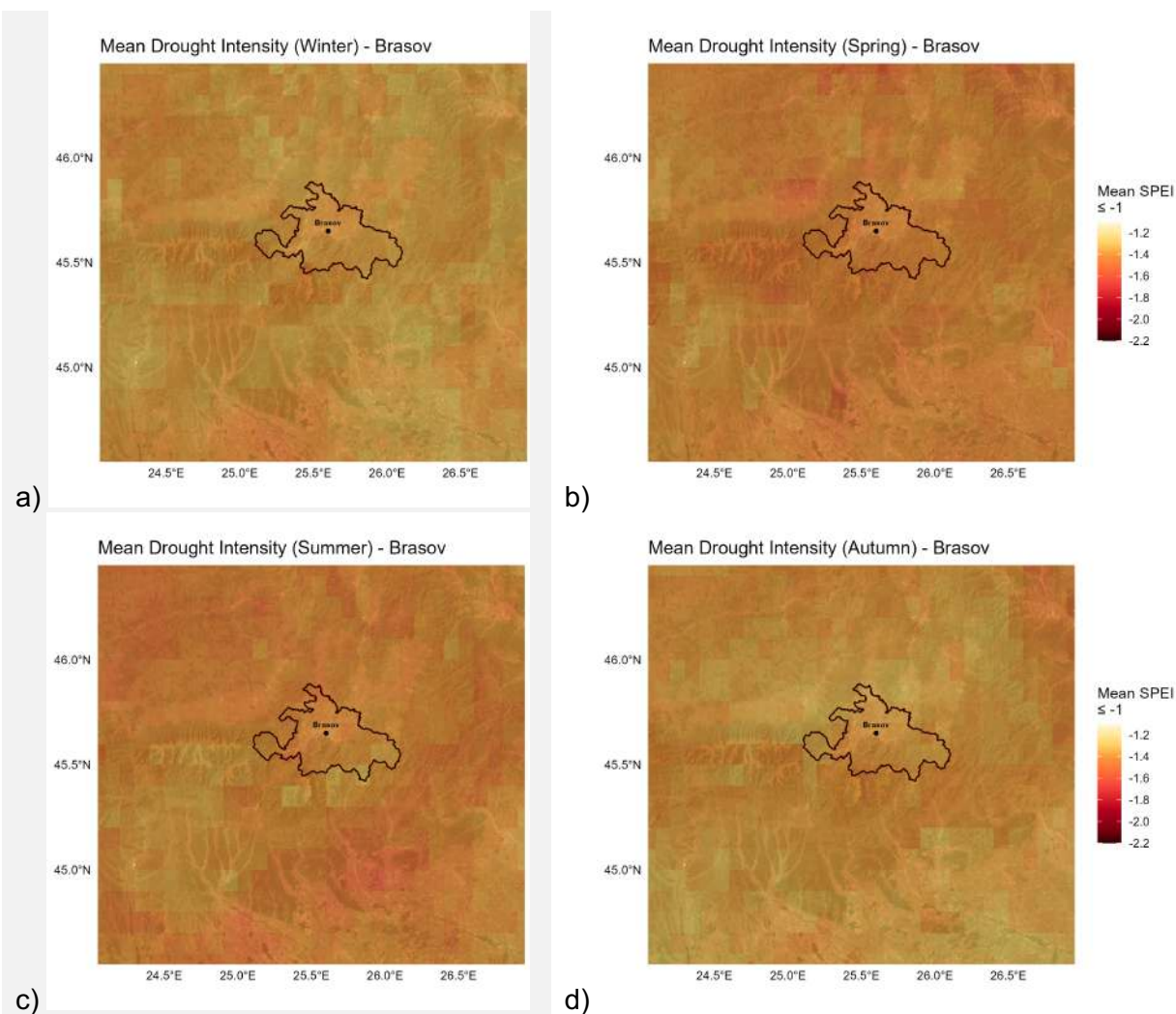


Figure A 30: Spatial distribution of seasonal drought intensity for the greater CSA Brasov area during 1990-2022 based on the SPEI-1 ≤ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.4.3.3 Prague

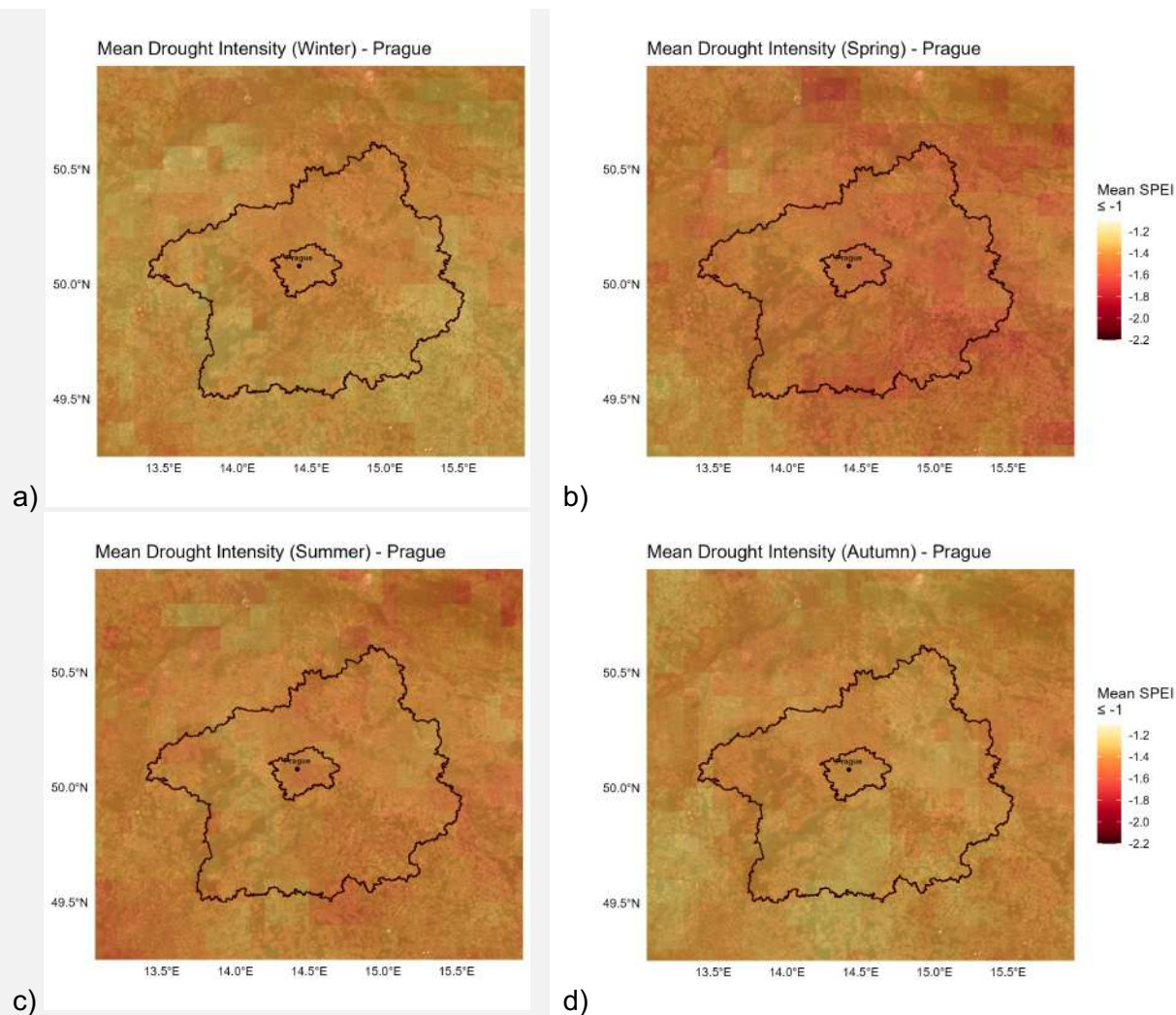


Figure A 31: Spatial distribution of seasonal drought intensity for the greater CSA Prague area during 1990-2022 based on the SPEI-1 ≤ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.4.4 Seasonal Wetness Maps

9.4.4.1 Leipzig

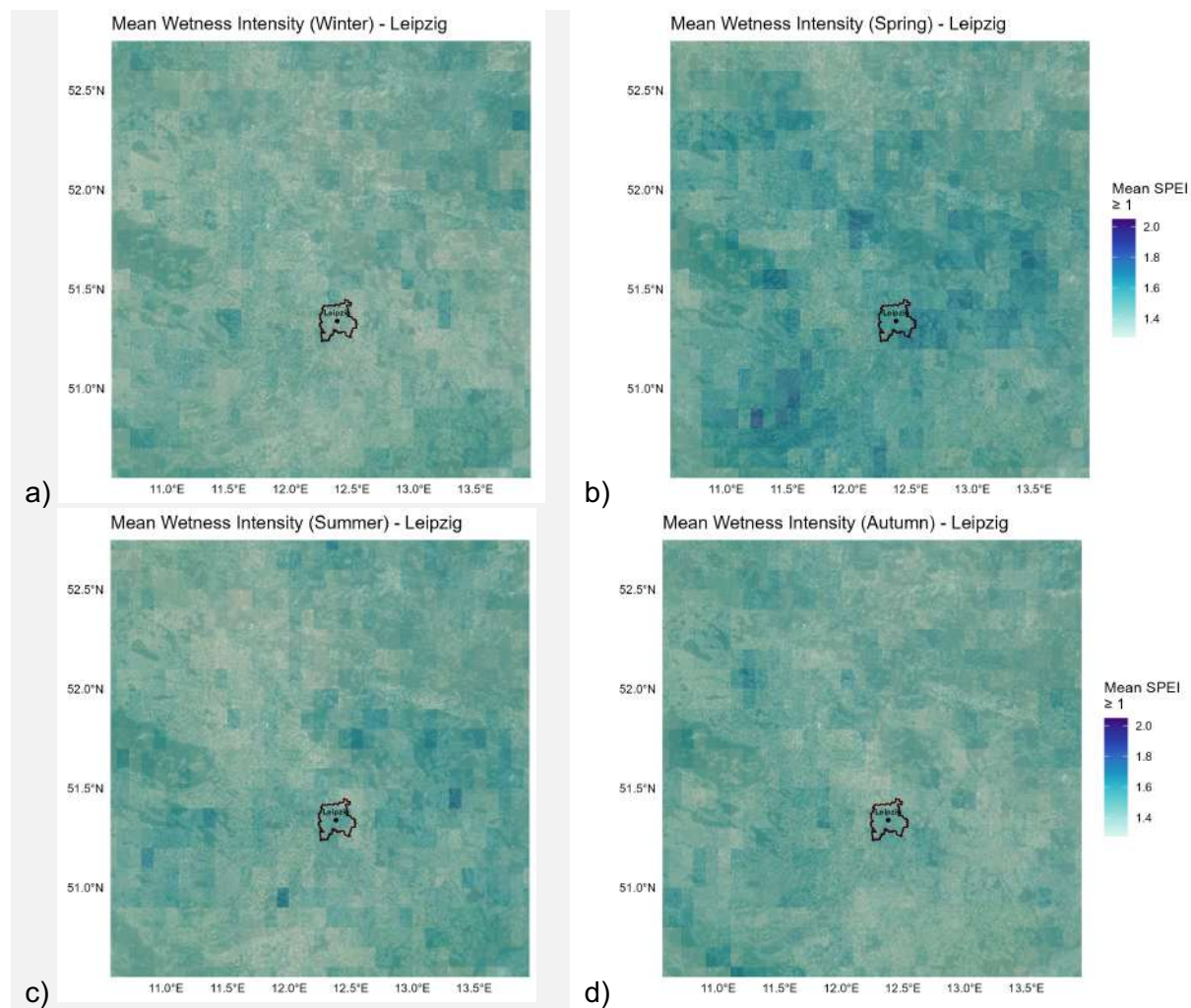


Figure A 32: Spatial distribution of seasonal wetness intensity for the greater CSA Leipzig area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.4.4.2 Funen-Odense

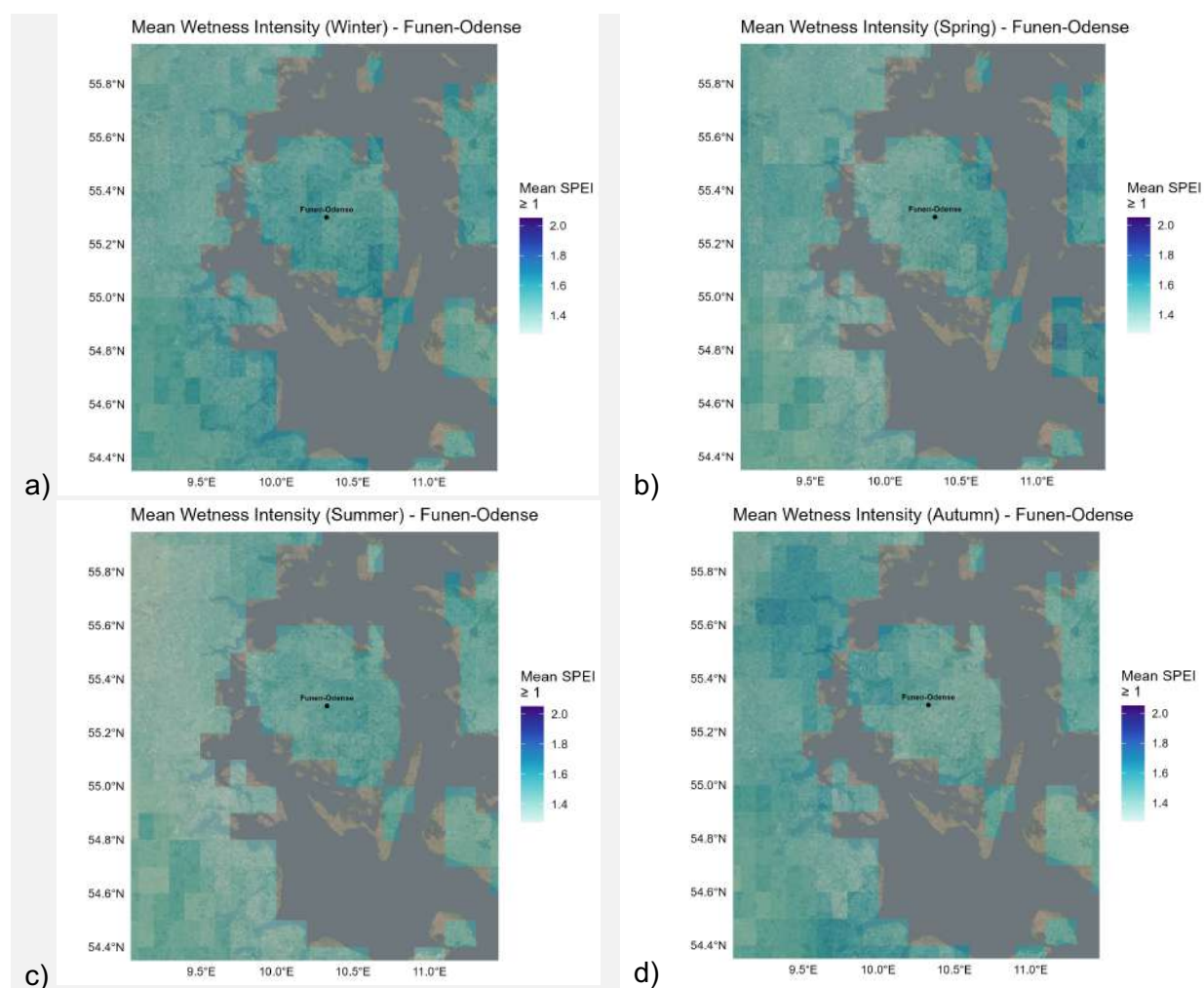


Figure A 33: Spatial distribution of seasonal wetness intensity for the greater CSA Funen-Odense area during 1990-2022 based on the $SPEI-1 \geq 1$ (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.4.4.3 Brasov

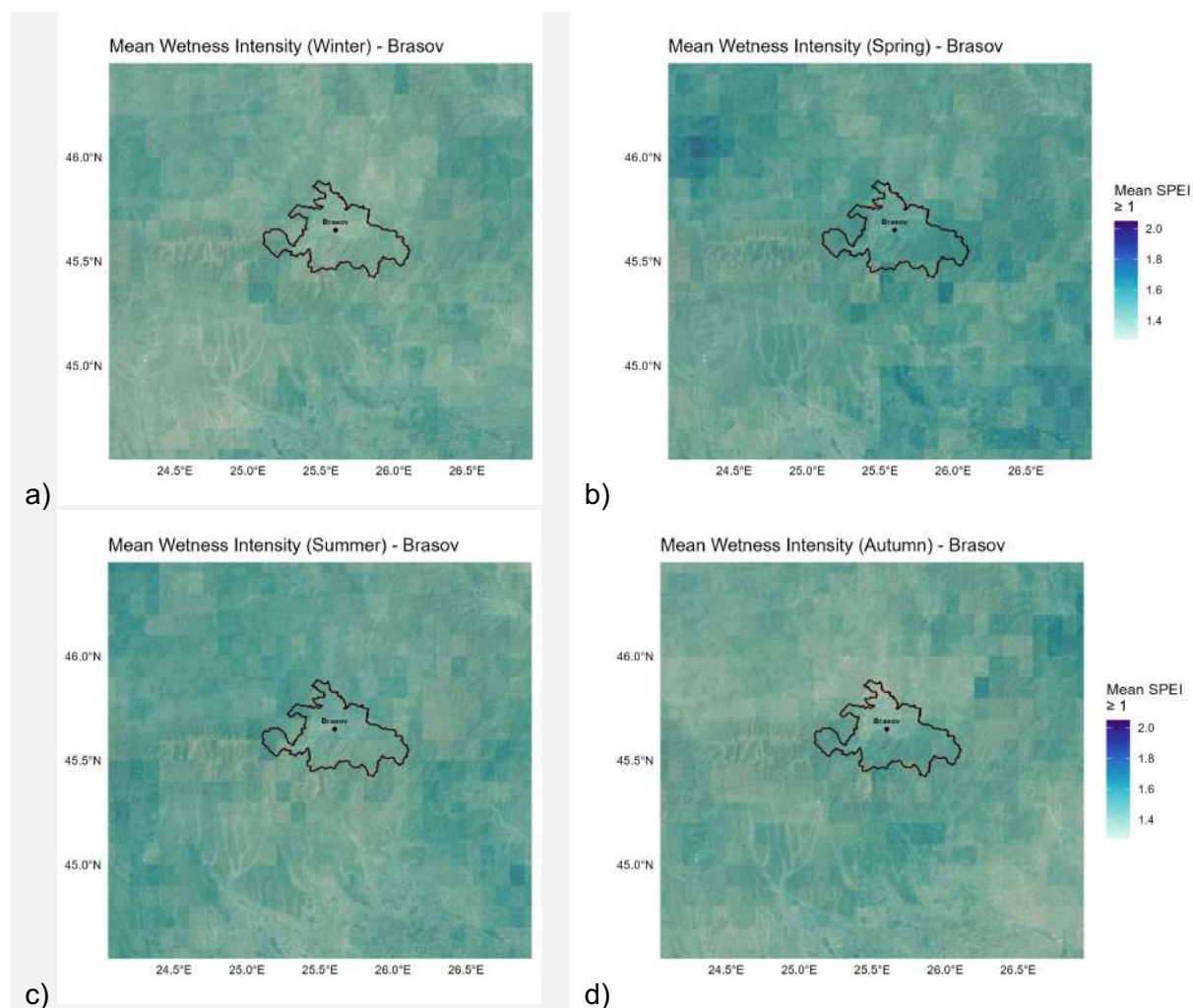


Figure A 34: Spatial distribution of seasonal wetness intensity for the greater CSA Brasov area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.4.4.4 Birmingham

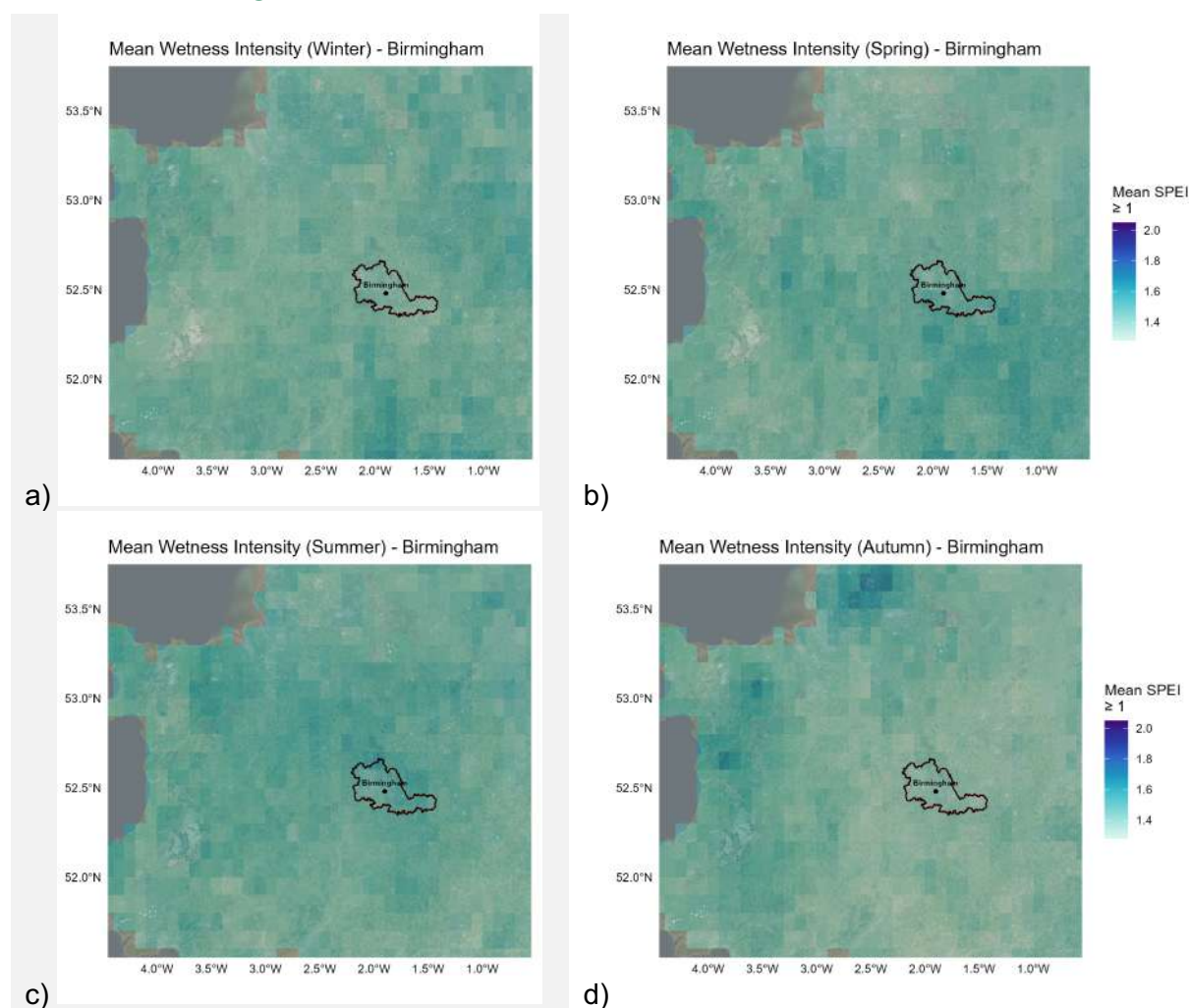


Figure A 35: Spatial distribution of seasonal wetness intensity for the greater CSA Birmingham area during 1990-2022 based on the SPEI-1 ≥ 1 (reference period 1992-2022) and PET calculated with the modified Hargreaves approach and E-OBS data, showing (a) Winter (DJF), (b) Spring (MAM), (c) Summer (JJA) and (d) Autumn (SON).

9.5 Comparative analysis of SPEI

This section presents a comparative temporal analysis of the SPEI results presented in the previous sections, derived from different datasets and PET formulations for the selected CSAs, highlighting similarities and differences in temporal variability and drought/wetness dynamics.

9.5.1 Athens

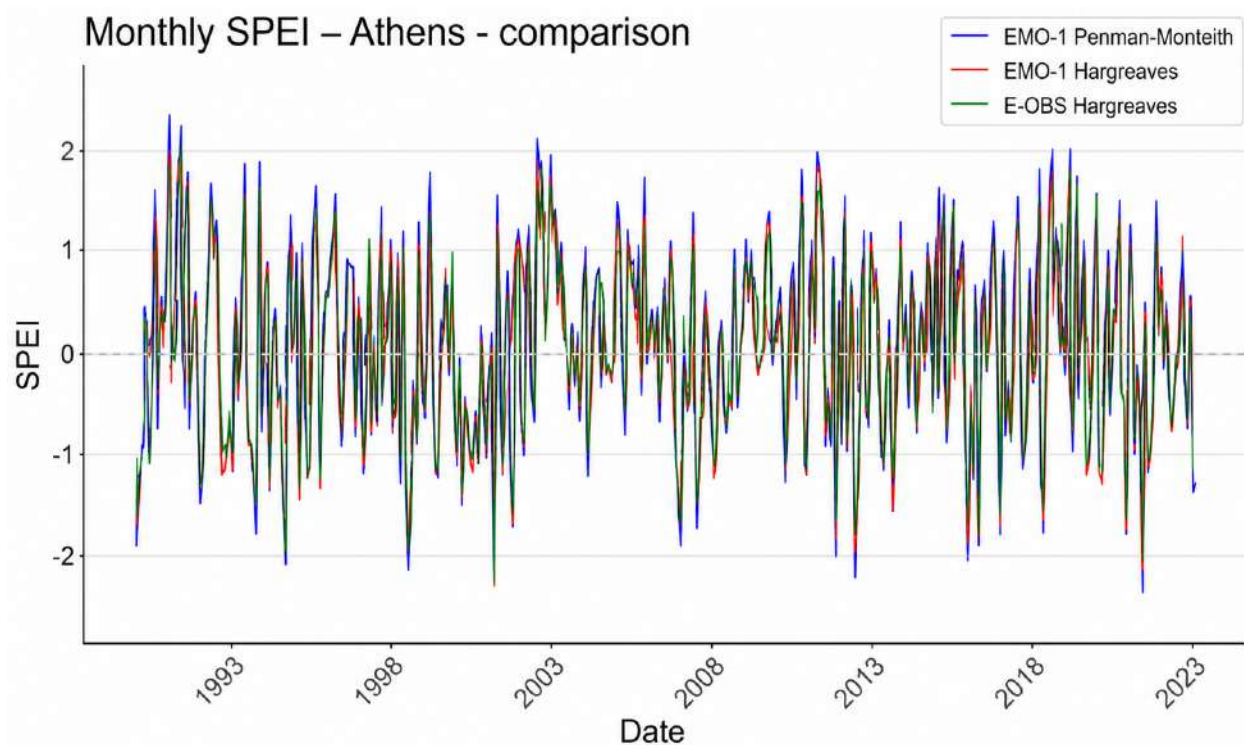


Figure A 36: Temporal comparison of monthly SPEI distributions for the greater CSA Athens area based on the EMO-1 Penman–Monteith, EMO-1 Modified Hargreaves, and E-OBS Modified Hargreaves approaches during the reference period 1990–2022.

9.5.2 Barcelona

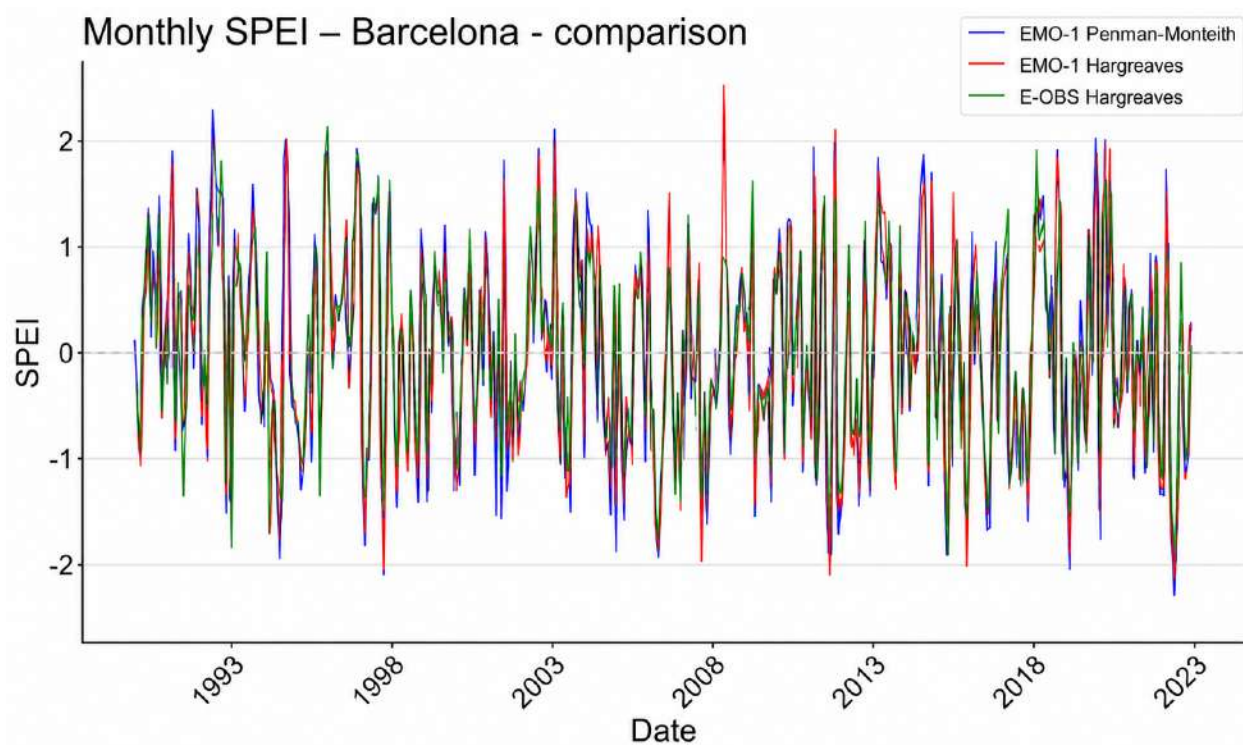


Figure A 37: Temporal comparison of monthly SPEI distributions for the greater CSA Barcelona area based on the EMO-1 Penman–Monteith, EMO-1 Modified Hargreaves, and E-OBS Modified Hargreaves approaches during the reference period 1990–2022.

9.5.3 Birmingham

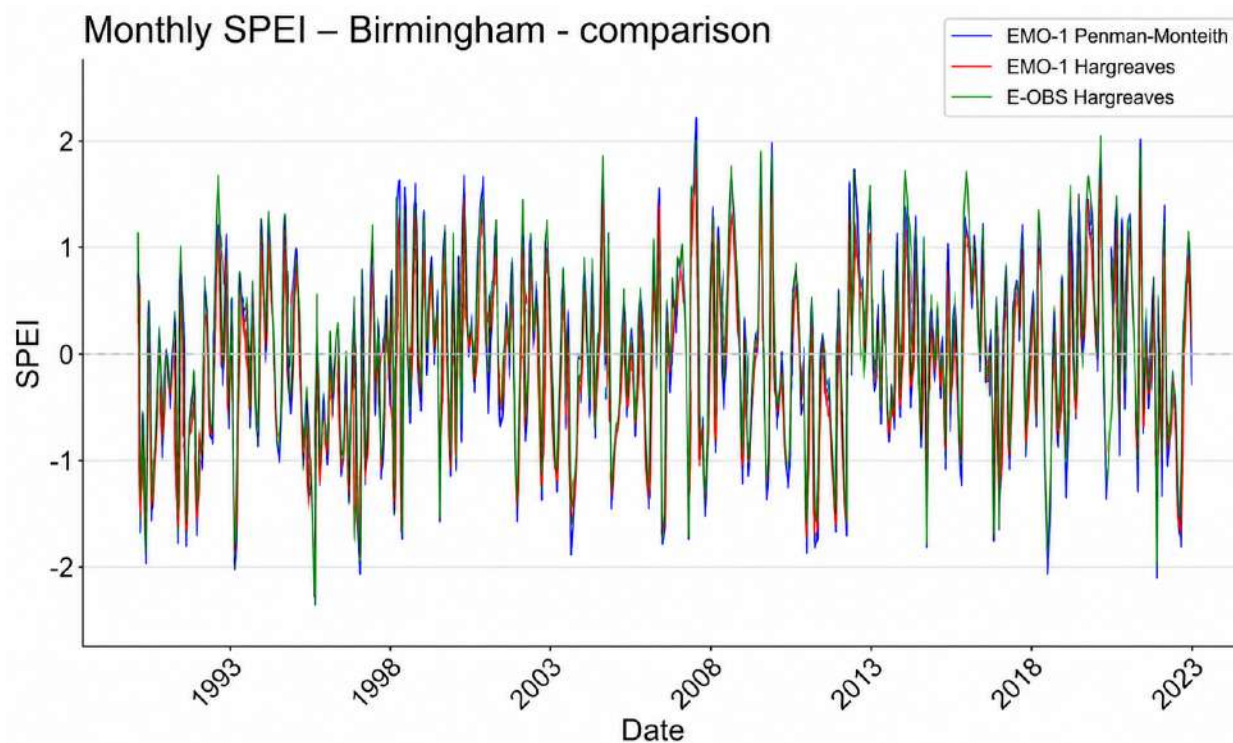
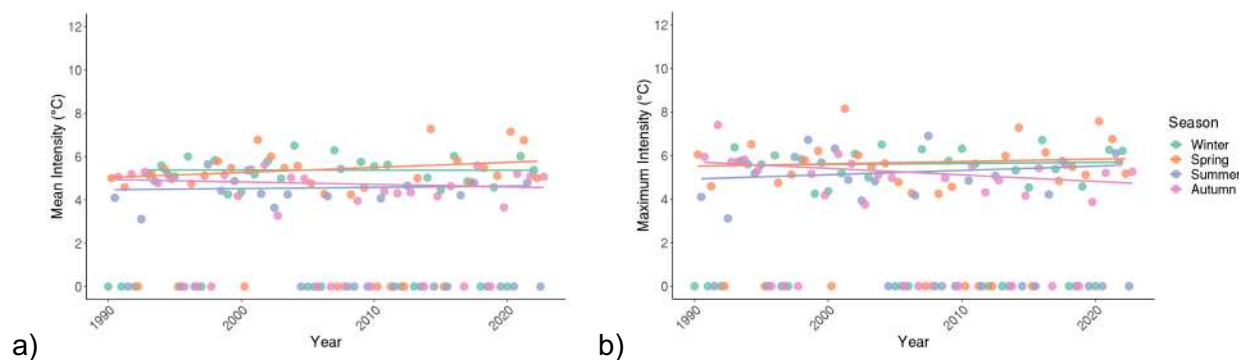
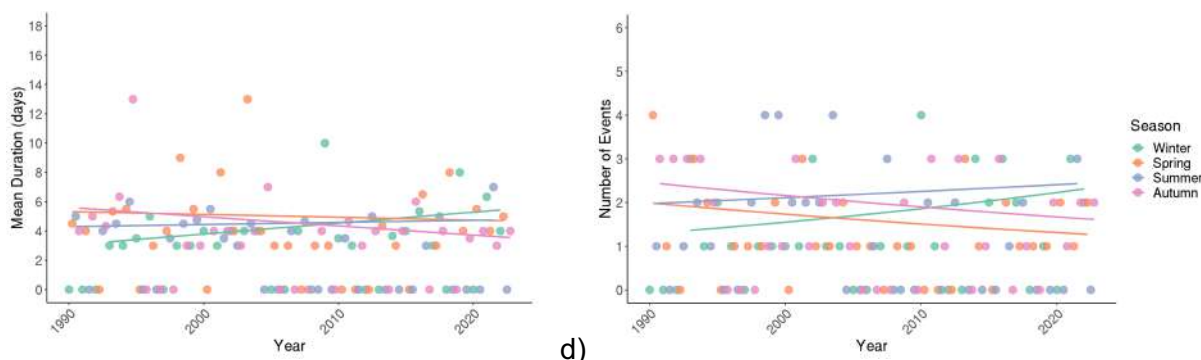


Figure A 38: Temporal comparison of monthly SPEI distributions for the greater CSA Birmingham area based on the EMO-1 Penman–Monteith, EMO-1 Modified Hargreaves, and E-OBS Modified Hargreaves approaches during the reference period 1990–2022.

9.6 Comparative assessment of Heatwave trend

9.6.1 Athens





c) d)
Figure A 39: Temporal distribution of heatwave metrics for the greater CSA Athens area on E-OBS, showing (a) mean cumulative intensity ($^{\circ}\text{C}$), (b) maximum intensity ($^{\circ}\text{C}$), (c) mean duration (days), and (d) mean occurrence of heatwave events for each season during the period 1990–2022. The trend for non-zero values for each season is estimated using linear regression, except for heatwave frequency, where a generalized linear model was applied.

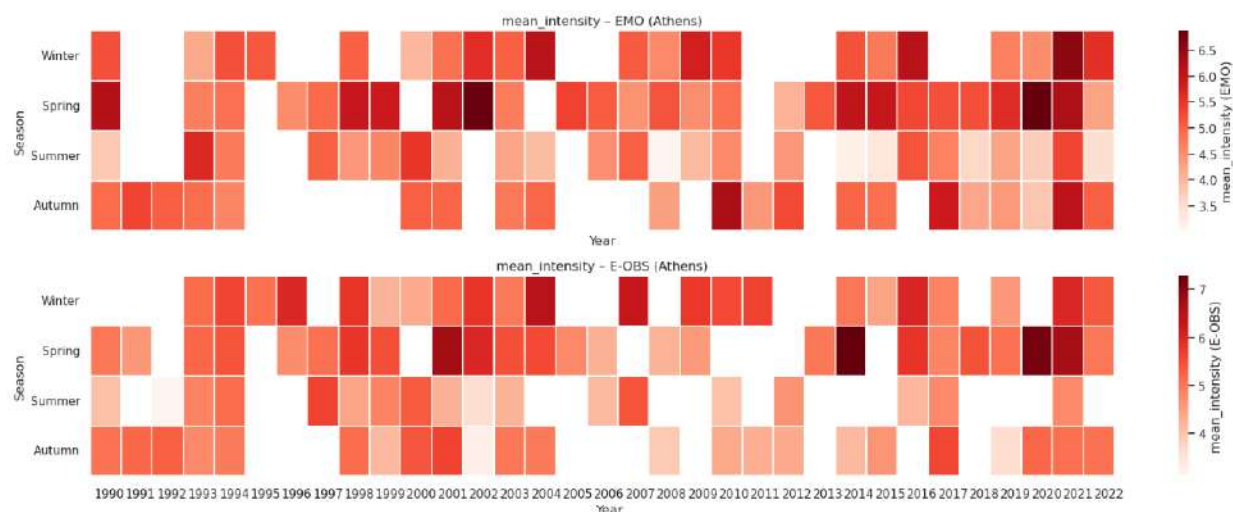


Figure A 40: Comparison of seasonal mean heatwave intensity for the greater CSA Athens area derived from the EMO-1 and E-OBS datasets during the reference period 1990–2022. The figure highlights the temporal variability of heatwave intensity across seasons and illustrates differences in heatwave detection associated with the spatial resolution of the underlying datasets.

9.7 Climate hazards indicators

A comprehensive list of climate-specific indices, inclusive a couple with novel developments, that focuses on individual types of natural hazards, such as floods, droughts, or heatwaves is provided in Table A1. These indicators quantify the physical intensity, frequency, and geographic distribution of a specific hazard.

Table A 1: Climate hazards indicators.

Index	Name	Description	Temporal resolution	Associated hazard	Applicability	References
BWHMD	Bivariate Heat Magnitude Day Index	Measures extreme heat events by combining maximum and minimum temperature data. It builds on the Heat Magnitude Day (HMD) and detects heat events lasting at least three days. The index requires two time series, one for maximum temperature (HMDTMAX) and one for minimum temperature (HMDTMIN). A supervised learning model then combines these two series into a single function, BVHMD, which is designed to reflect socio-economic impacts.	Daily	Heatwaves	Detection of heatwaves and classification of their cumulative magnitude. Examination of heatwaves and associated impacts (e.g. socio-economic aspects, yield).	Luther et al. (in prep.)
CDD	Consecutive dry days	Maximum length of dry spell (consecutive days with $RR < 1\text{mm}$)	Daily	Droughts	Characterization of dry weather spell and associated drought events. Examination of drought events/ drying conditions and associated impacts (e.g. on yield, health, water resources). Changes in dry spell duration and spatio-temporal variability. Response of dry spells to warming temperature and possible mechanisms. Climate mitigation and adaptation. Disaster Risk Reduction. Vulnerability assessment.	Climpact (2025), Li et al. (2021), Lima et al. (2023), Oikonomou et al. (2010), Wang et al. (2021).

CSI	Combined Stress Index	Typically calculated by combining relevant indices e.g. as a simple linear combination of the standardized HMD and SPEI (may require impact data).	Monthly/Annual	Multi-hazard (Heatwave, Drought, etc.)	A metric used to assess the cumulative impact of multiple environmental and/or climatic stressors, such as drought, heatwaves, excessive rainfall, on ecosystems, agriculture, human health, among others.	Zampieri et al. (2017).
CWD	Consecutive Wet Days	Maximum length of wet spell: maximum number of consecutive days with RR $\geq$ 1mm	Daily	Floods	Characterization of wet weather spell and associated flood events. Climate disaster risk management, climate mitigation and adaptation. Flash flood hazard measurement and modelling.	Climapact (2025), Murray et al. (2021), Wang et al. (2021).
EHF	Excess Heat Factor	The combined effect of Excess Heat and Heat Stress calculated as an index provides a comparative measure of intensity, load, duration and spatial distribution of a heatwave event.	Daily	Heatwaves	Monitoring of meteorological and health heatwave impact situations. Epidemiological studies. Bio-meteorological Index to characterise heat risk. Climate, diagnostics, multi-day, S2S and projection forecasts.	Handbook of Extreme Heat Indicators and Indices, Murray et al. (2021), Nairn & Fawcett (2013).
Heat index	Heat index	A heat stress indicator used by the NOAA National Weather Service. It is calculated using multiple linear regression based on daily maximum temperature and relative humidity (calculated from daily mean specific humidity and surface pressure).	Hourly/Daily	Heatwaves	Human energy-budget based index to characterise heat risk. Early warning systems.	Climate Data Store (2025), Murray et al. (2021).

HMD	Heat Magnitude Day	The Heat Magnitude Day (HMD) is defined as the cumulative maximum temperature exceedances during heatwave events (during month(s), season(s), year(s)), where a heatwave is commonly defined as event on which the daily maximum temperature exceeds the long-term 90th percentile for at least three consecutive days.	Daily	Heatwaves	The index can be implemented for the study of sectoral impacts, such as agricultural productivity, due to the concept of cumulative exceedances that can consider the impact of persistence.	Zampieri et al. (2017).
Humidex	Humidex	A heat stress indicator used by Canadian meteorological services. It is calculated as linear combination of daily maximum temperature and vapour pressure (calculated from daily mean specific humidity and surface pressure).	Hourly/ Daily	Heatwaves	Human energy-budget based index to characterise heat risk. Early warning systems.	Climate Data Store (2025), Murray et al. (2021).
HWA (EHF/Tx 90/Tn90)	Heatwave amplitude as defined by either the Excess Heat Factor (EHF), 90th percentile of TX or the 90th percentile of TN	The peak daily value in the hottest heatwave (defined as the heatwave with the highest HWM).	Daily	Heatwaves	Examination of heatwaves (temporal and spatial distribution) and associated impacts (e.g. on yield, health, water resources). Monitoring a potential increase in the intensity of heatwaves --> conclusions about climate change impacts. Projecting characteristics of heatwaves to advance prediction skills and offer reliable early warnings to the public. Disaster Risk Reduction.	Al-Yaari et al. (2023), Climapact (2025), Perkins & Alexander (2013).

HWD (EHF/Tx 90/Tn90)	Heatwave duration as defined by either the Excess Heat Factor (EHF), 90th percentile of TX or the 90th percentile of TN	The length of the longest heatwave identified by HWN.	Daily	Heatwaves	Examination of heatwaves (temporal and spatial distribution) and associated impacts (e.g. on yield, health, water resources). Monitoring a potential increase in the intensity of heatwaves --> conclusions about climate change impacts. Projecting characteristics of heatwaves to advance prediction skills and offer reliable early warnings to the public. Disaster Risk Reduction.	Al-Yaari et al. (2023), Climpact (2025), Perkins & Alexander (2013).
HWF (EHF/Tx 90/Tn90)	Heatwave frequency as defined by either the Excess Heat Factor (EHF), 90th percentile of TX or the 90th percentile of TN	The number of days that contribute to heatwaves, as defined by HWN.	Daily	Heatwaves	Examination of heatwaves (temporal and spatial distribution) and associated impacts (e.g. on yield, health, water resources). Monitoring a potential increase in the intensity of heatwaves --> conclusions about climate change impacts. Projecting characteristics of heatwaves to advance prediction skills and offer reliable early warnings to the public. Disaster Risk Reduction.	Al-Yaari et al. (2023), Climpact (2025), Perkins & Alexander (2013).

HWM (EHF/Tx 90/Tn90)	Heatwave magnitude as defined by either the Excess Heat Factor (EHF), 90th percentile of TX or the 90th percentile of TN	The mean temperature of all heatwaves identified by HWN.	Daily/ Monthly	Heatwaves	Examination of heatwaves (temporal and spatial distribution) and associated impacts (e.g. on yield, health, water resources). Monitoring a potential increase in the intensity of heatwaves --> conclusions about climate change impacts. Projecting characteristics of heatwaves to advance prediction skills and offer reliable early warnings to the public. Disaster Risk Reduction.	Al-Yaari et al. (2023), Climpact (2025), Perkins & Alexander (2013).
HWN (EHF/Tx 90/Tn90)	Heatwave number as defined by either the Excess Heat Factor (EHF), 90th percentile of TX or the 90th percentile of TN	The number of individual heatwaves that occur each summer (Nov–Mar in southern hemisphere and May–Sep in northern hemisphere).	Monthly/ Annual	Heatwaves	Examination of heatwaves (temporal and spatial distribution) and associated impacts (e.g. on yield, health, water resources). Monitoring a potential increase in the intensity of heatwaves --> conclusions about climate change impacts. Projecting characteristics of heatwaves to advance prediction skills and offer reliable early warnings to the public. Disaster Risk Reduction.	Al-Yaari et al. (2023), Climpact (2025), Perkins & Alexander (2013).

NPSPEI	Non-parametric Standardized Precipitation Evapotranspiration Index	The NPSPEI is a nonparametric variant of the SPEI that replaces the parametric log-logistic distribution with a kernel-based estimator of the water balance distribution function. The new index uses unbounded kernels to estimate the distribution, it can thus assign probabilities to any value, even those beyond the original training (reference) period. This helps avoid issues with extrapolation and better captures extremes.	Monthly	Drought	Captures wet and dry conditions. Positive (negative) values coincide with wet (dry) conditions. Droughts are identified when the NPSPEI drops below -1.	Luther et al. (in prep.)
PET	Physiological equivalent temperature	Derived from the human energy balance equation. Dry temperature, relative humidity, windspeed, and mean radiant temperature are used to calculate PET.	Hourly/Daily	Heatwaves	Human energy-budget based index to characterise heat risk.	Murray et al. (2021), Zare (2018).
PRCPTOT	Annual total precipitation on wet days	Total accumulated precipitation from “wet days” during the period of interest.	Annual	Floods	Examination (extreme) rainfall events (temporal and spatial distribution) and associated impacts (e.g. on yield, water resources). Water resource forecast (under climate change) --> sustainable water resource development. Vulnerability assessment.	Climpact (2025), Kouman et al. (2022), Li et al. (2021).
R10mm	Number of very heavy rain days	Annual count of days when PRCP $\geq$ 20 mm.	Annual	Floods	Examination of (extreme) rainfall events (temporal and spatial distribution) and associated impacts (e.g. on heavy precipitation-related disasters). Vulnerability assessment.	Climpact (2025), Xiang-Ling et al. (2020).

R20mm	Number of very heavy rain days	Number of days per year with 20 mm or more precipitation. Precipitation is deposition of water on the Earth's surface, either rain, snow, ice or hail.	Annual	Floods	Examination of extreme rainfall events (occurrence, duration, and severity) and associated impacts (e.g. on yield, water resources). Vulnerability assessment.	Climate Data Store (2025), Climapact (2025), Reddy et al. (2023).
R95pTOT	Contribution from very wet days	Contribution to total precipitation from very wet days.	Monthly/Annual	Floods	Examination extreme rainfall events (temporal and spatial distribution) and associated impacts (e.g. on yield, water resources). Detection of a disproportional increase of extreme precipitation amounts, relative to the total precipitation. Vulnerability assessment.	Climapact (2025), ETCCDI (2025), Leander et al. (2014).
R99pTOT	Contribution from extremely wet days	Contribution to total precipitation from extremely wet days.	Monthly/Annual	Floods	Examination extreme rainfall events (temporal and spatial distribution) and associated impacts (e.g. on yield, water resources). Detection of a disproportional increase of extreme precipitation amounts, relative to the total precipitation. Vulnerability assessment.	Climapact (2025), ETCCDI (2025), Zarrin & Dadashi-Roudbari (2022).
Rx1day	Maximum 1-day precipitation on	Maximum daily precipitation during the period of interest	Daily	Floods	Examination of (extreme) rainfall events (temporal and spatial distribution) and associated impacts (e.g. on yield). Vulnerability assessment. Disaster Risk Reduction.	Climapact (2025), Valverde & Marengo (2014).

Rx5day	Maximum consecutive 5-day precipitation	Maximum precipitation over consecutive 5-day during the period of interest.	Daily	Floods	Examination of (extreme) rainfall events (temporal and spatial distribution) and associated impacts (e.g. on yield). Vulnerability assessment. Disaster Risk Reduction.	Climpact (2025), Valverde & Marengo (2014).
Rxdday	User-defined consecutive days PR amount	Maximum d-day PR total.	User-defined	Floods	Examination (extreme) rainfall events (temporal and spatial distribution) and associated impacts (e.g. on yield, health, water resources). Disaster Risk Reduction	Climpact (2025).
SDII	Simple precipitation intensity index	Indicates the average daily rainfall for a period.	Monthly/Annual	Floods	Examination (extreme) rainfall events (temporal and spatial distribution) and associated impacts (e.g. on water resources).	Climpact (2025).
SET	Standard effective temperature	Rational index which is calculated by taking skin temperature and skin wetness into account.	Hourly/Daily	Heatwaves	Human energy-budget based index to characterise heat risk.	Murray et al (2021), Zare et al. (2018).
SLA	Sea Level Anomaly	Measures deviations in sea level from a long-term mean baseline. These anomalies are derived from satellite altimetry and tide gauge data, capturing changes caused by factors such as thermal expansion, land ice melt and changing ocean currents.	Monthly/Annual	Coastal Floods, Tsunamis, Saltwater intrusion	Monitoring and predicting coastal hazards, sea-level rise, and its impacts on coastal communities and ecosystems. Coastal resilience projects. Flood early warning systems.	Ganguli & Merz (2019), Climate Change Initiative Coastal Sea Level Team (2020).
SMI	Soil Moisture Index	Is defined as the proportion of the difference between the current soil moisture and the permanent wilting point to the field capacity and the residual soil moisture. Values range from 0 to 1 with 0 indicating	Daily/Weekly/Monthly	Drought, Flood	Drought Hazard classification offering a measure of water availability in the soil. Crop irrigation management. Drought forecasting. Understanding and mitigating the impacts of droughts and	Saha et al. (2018).

		extreme dry conditions and 1 indicating extreme wet conditions.			supporting sustainable resource management.	
SPEI	Standardised Precipitation on Evapotranspiration Index	Considers both precipitation and evapotranspiration to assess drought severity and duration. Due to its multi-scalar nature, it can be used by different scientific disciplines to detect, monitor, and analyze droughts. It provides a flexible measure of drought across time scales of 3, 6, and 12 months, capturing the balance between water supply (precipitation) and demand (evaporation). This makes it suitable for evaluating various types of droughts, from agricultural to hydrological.	Monthly/Annual	Drought	Detection and assessment of dry events and associated impacts (e.g. on health, agriculture). Identification of drought types, severity and impacts on diverse systems. Studies of the effect of global warming on drought severity. Disaster Risk Reduction.	Climpact (2025), Climate Data Guide (2025), Li et al. (2015).
SPI	Standardised Precipitation Index	Widely used tool for assessing precipitation anomalies relative to a long-term record, providing a measure of wet or dry periods. It is effective for characterizing meteorological drought across timescales: short-term SPI (1–3 months) reflects soil moisture conditions, while long-term SPI (6–12 months) relates to groundwater and reservoir storage.	Monthly/Annual	Droughts, Floods	Detection and assessment of dry events and associated impacts (e.g. on health, agriculture). Evaluation of drought severity and duration for both agricultural and hydrological contexts. Drought monitoring and early warning efforts. Quantification of precipitation deficit and drought impact on the availability of the different water resources. Disaster Risk Reduction.	Climpact (2025), NASA (2025), Murray et al. (2021), WMO (2012).
SU	Number of summer days	Annual count of days when $T_X > 25^{\circ}\text{C}$.	Annual	Heatwaves	Detection and assessment of extreme temperature events and associated impacts (e.g. on	Climpact (2025).

					health). Disaster Risk Reduction.	
TR	Number of Tropical Nights	Annual count of days when $TN > 20^{\circ}\text{C}$.	Annual	Heatwaves	Detection and assessment of extreme temperature events and associated impacts (e.g. on health, agriculture). One of the indicators of climate change. Disaster Risk Reduction. Vulnerability assessment.	Climpact (2025), Climate ADAPR (2025), Kim et al. (2017).
TX95t	Very warm day threshold	The value of the 95th percentile of TX.	Daily	Heatwaves	Detection and assessment of extreme temperature events and associated impacts (e.g. on yield, health).	Climpact (2025), Herold et al. (2018), Singh & Mall (2023).
TXdTNd	User- defined consecutive number of hot days and nights	Annual count of d consecutive days where both $TX > 95\text{th}$ percentile and $TN > 95\text{th}$ percentile, where $10 \geq d \geq 2$.	User- defined	Heatwaves	Examination of extreme temperature events and associated impacts (e.g. on yield, health, water resources). User-defined adjustment of the TXdTNd for specific application (e.g. certain crops or other sector- specific requests). Disaster Risk Reduction.	Climpact (2025), Herold et al. (2018).
TXge30	TX of at least 30°C	Number of days when $TX \geq 30^{\circ}\text{C}$.	Daily/ Monthly/ Annual	Heatwaves	Examination of extreme temperature events and associated impacts (e.g. on yield, health). Quantifying the relationship between heat and health, as well effects of heat stress on crops. Future projections.	Climpact (2025), Herold et al. (2018).

TXge35	TX of at least 35 °C	Number of days when TX $\geq$ 35 °C.	Daily/ Monthly/ Annual	Heatwaves	Examination of extreme temperature events and associated impacts (e.g. on yield, health). Quantifying the relationship between heat and health. Future projections. Disaster Risk Reduction.	Climpact (2025), Herold et al. (2018).
TXgt50p	Percentage of days with temperature above the median	Percentage of days when TX > 50th percentile.	Monthly/ Annual	Heatwaves	Detection of warming trends and associated impacts (e.g. on yield, health, water resources).	Climpact (2025), Herold et al. (2018), Khan et al. (2022), Villa-Falfán et al. (2023).
TXn	Minimum value of daily maximum temperature	Minimum value of daily maximum temperature for the sample period.	Daily	Heatwaves	Detection and assessment of extreme temperature events and associated impacts (e.g. on yield). Detection of trends in temperature extremes. The trends can be detected in terms of the temperature values and/or the waiting times to a new extreme. Easy comparison of monthly peak maximum temperature values of previous years.	Climpact (2025), Handbook of Extreme Heat Indicators and Indices, Herold et al. (2018), Uni-Hamburg (2023).
TXx	Maximum value of daily maximum temperature	Maximum value of daily maximum temperature for the sample period (x = month or year).	Daily	Heatwaves	Detection and assessment of extreme temperature events and associated impacts (e.g. on yield). Indication how the right most tail of the probability distribution will change in the future. Detection of trends in temperature extremes. The trends can be detected in terms of the temperature values and/or the waiting times to a new	Climpact (2025), Herold et al. (2018), Handbook of Extreme Heat Indicators and Indices, Uni-Hamburg (2023).

					extreme. Disaster Risk Reduction.	
UTCI	Universal thermal climate index	The equivalent temperature for the environment derived from a reference environment. It is defined as the air temperature of the reference environment which produces the same strain index value in comparison with the reference individual's response to the real environment.	Hourly/ Daily	Heatwaves	Assessing heat stress in outdoor spaces. Human energy-budget based index to characterise heat risk.	Murray et al (2021), Zare et al (2018).
Wet- bulb temperature	Wet-bulb temperature	The wet-bulb temperature index is a heat stress indicator that indicates the human cooling capacity through sweating. It is calculated from the equivalent potential temperature based on daily maximum temperature and water vapour mixing ratio (calculated from daily mean specific humidity and surface pressure).	Hourly/ Daily	Heatwaves	Holistic index to characterise heat risk. Early warning systems.	Climate Data Store (2025), Murray et al. (2021).
Wind direction	Wind direction	The direction of wind flow over a specific period of time is measured. In addition to providing critical insights into atmospheric circulation patterns, it is also commonly combined with wind speed data to aid in weather forecasting, aviation, maritime navigation, and renewable energy planning.	Hourly/ Daily	Storms, hurricanes, and strong winds Dispersion of dust storms, volcanic ash and coastal floods	Storm path prediction systems.	Lee (2006).

Wind speed	Wind speed	Measures the velocity of wind over a specific area and time frame, allowing for a more accurate prediction of storm intensity, as well as optimal planning of wind-related infrastructure and monitoring of weather patterns.	Hourly/Daily	Storms, hurricanes, and strong winds Dispersion of dust storms, volcanic ash and coastal floods	Storm prediction systems. Wind energy optimization. Early warning systems.	Lee (2006), Murray et al. (2021).
WSDI	Warm spell duration Index	Annual count of days with at least 6 consecutive days when TX > 90th percentile	Annual	Heatwaves	Detection and assessment of temperature extremes with respect to climate change and associated impacts (e.g. on yield, health, water resources). Climate diagnostic tool: commonly used in climate studies, suitable for environmental analysis, less applicable for human and infrastructure which are adapted to annual extreme thresholds. Disaster Risk Reduction.	Climpact (2025), Handbook of Extreme Heat Indicators and Indices, Lu et al. (2018).
WSDId	User-defined WSDI	Annual number of days contributing to events where d or more consecutive days experience TX > 90th percentile.	Annual	Heatwaves	Detection and assessment of temperature extremes with respect to climate change and associated impacts (e.g. on yield, health, water resources). Climate diagnostic tool: commonly used in climate studies, suitable for environmental analysis, less applicable for human and infrastructure which are adapted to annual extreme thresholds.	Climpact (2025), Lu et al. (2018).

				User-defined adjustment of the WSDI for specific application (e.g. certain crops or other sector- specific requests)	
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9.8 Disaster risk indicators

The set of disaster risk indicators presented here stem from the Bureau of the Conference of European Statisticians (CES) Task Force on Measuring Hazardous Events and Disasters, established in 2020 that developed a pilot set of core disaster-risk indicators to guide national statistical offices in regularly producing disaster-related data. Focused on measuring disaster risk, especially vulnerability, exposure, and coping capacity, the indicators cover hazards with existing monitoring systems (e.g. meteorological, hydrological, geohazards). Endorsed in 2023 and updated after 2024 consultations, the indicators aim to improve evidence, comparability, and data harmonization for disaster risk and support global frameworks like the SDGs, Sendai Framework, and Paris Agreement.

Table A 2: Set of Core Disaster-Risk-Related Indicators after the United Nations Economic Commission for Europe 2025. Primary elements at risk are abbreviated as follows: P – People; H – Housing; BS – Basic services; CI – Critical infrastructure; EA – Economic activity; Ec – Ecosystems; F – Food security and agriculture; W – Water security; En – Energy security; He – Health care; CH – Cultural heritage; G – Governance. All indicators are classified into three tiers based on their level of methodological development and the availability of data at the global level, as follows. Tier 1: Indicator is conceptually clear, an internationally established methodology and standards are available, and data are regularly produced by at least 50 per cent of countries, for every region where the indicator is relevant. Tier 2: Indicator is conceptually clear, an internationally established methodology and standards are available, but data are not regularly produced by countries. Tier 3: Internationally established methodology or standards are not yet available, but methodology/standards are being (or will be) developed or tested.

Indicator	Primary elements at risk	Comments	Tier	Methodology
Dimensions of hazards				
Number of hazardous events per year (per type of hazard)	P; H; B S; C I; E A; E c; F; W; E n; H e; C H; G	Internationally recommended threshold values for other (than hydrometeorological) types of hazards to be developed, countries should use national threshold values in the meantime; tier depends on type of hazard	1-3	WME CHE for hydrometeorological hazards: Guidance for hydrometeorological hazards is currently being finalised: https://community.wmo.int/meetings/wmo-workshop-finalization-cataloguing-hazardous-weather-water-climate-and-space-weather-events-implementation-plan-che
Proportion of hazardous events with deaths per year (per type of hazard).	P; G	Tier depends on type of hazard	1-3	WME CHE for hydrometeorological hazards: Guidance for hydrometeorological hazards is currently being finalised: https://community.wmo.int/meetings/wmo-workshop-finalization-cataloguing-hazardous-weather-water-climate-and-space-weather-events-implementation-plan-che

				climate-and-space-weather-events-implementation-plan-che
Proportion of coastal areas vulnerable to sea level rise	P; H; B S; C I; E A; E c; F; W; E n; H e; C H	Even if this is a very specific indicator, it is one of the very few indicators that may anticipate the location of future impact with accuracy, thus can help to plan accordingly. If the potentially affected area is defined, it is possible to estimate the number of houses, people etc. at risk.	2	Bondesanf et al. (1995).
Disaster Risk Reduction Activity				
Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies (SDG 1.5.4, SF E-2))	P; H; B S; C I; E A; E c; F; W; E n; H e; C H; G		2	SDG and SF: https://unstats.un.org/sdgs/metadata/ and https://www.undrr.org/publication/technical-guidance-monitoring-and-reporting-progress-achieving-global-targets-sandai
Proportion of government expenditure on DRR in relation to GDP	P; H; B S; C I; E A; E c; F; W; E n; H e; C H; G	In addition to the total government expenditure a distinction could be made between central government expenditure and local government expenditure	3	See e.g. national example of Indon+B4:C5
Proportion of curriculum (hours) in schools dealing with disaster risk in relation to total hours	P		2	Data owned by national government and/or lower levels of government that have jurisdiction on this issue
Proportion of government expenditure in early warning or Early Warning Systems (EWS) in relation to GDP	P	There is a caveat that many of EWS may have huge expenditure in the initial investment, and mainly maintenance cost afterwards.	2	Data owned by government

Proportion of government expenditure on risk awareness programs in relation to GDP	P	There is a need to define what can be considered as risk awareness programs.	3	Data owned by government
Proportion of municipalities with land use plans with consideration of disaster risk in relation to total land use plans.	P; H; B S; C I; E A; E c; F; W; E n; H e; C H; G		2	Data owned by national government and/or lower levels of government that have jurisdiction on this issue
Exposure				
Proportion of population living in hazard prone areas in relation to total population	P; H	Aggregate of global CC indicators 100 and 102; should be presented by types of major hazards	2	CC
Proportion of population living in areas affected by projected 1 m sea-level rise	P; H		2	Bondesanf et al. (1995).
Proportion of dwellings located in hazard prone areas in relation to total dwellings	H	Could be presented by types of major hazards; has a wider scope in terms of hazards than CC 92 (Buildings (settlements) vulnerable to climate change)	2	Dependent on mapping of hazard prone areas
Proportion of road infrastructure (km) located in hazard-prone areas in relation to total road infrastructure (km)	B S; C I	Could be presented by types of major hazards; Possible disaggregation of the indicator by type of road. Countries could produce complementary indicators for other types of transportation infrastructure (railroad, aviation, sea navigation).	2	UNDP: PDNA Transport: https://www.undp.org/sites/g/files/zskgke326/files/publications/PDNA_Transport_FIN_AL.pdf
Proportion of farmland in hazard-prone areas in relation to total farmland	F	Could be presented by types of major hazards	2	dependent on mapping of hazard prone areas

Proportion of number of hospital beds in hazard-prone areas in relation to total beds	B S; C I; H e		2	dependent on mapping of hazard prone areas
Proportion of population supplied by water supply industry (ISIC 36) in relation to total population in hazard prone areas	BS		2	IRWS, and dependent on mapping of hazard prone areas: https://unstats.un.org/unsd/publication/seriesM/seriesm_91e.pdf
Vulnerability				
Proportion of population living below the international poverty line, by sex, age, employment status and geographic location (SDG 1.1.1)	P		1	SDG and CC
Old-age dependency ratio	P		1	Eurostat: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Old-age_dependency_ratio
Proportion of energy consumed from thermal, nuclear and hydroelectric power plants in relation to total final energy consumption	B S; E n	WMO warned in its report (WMO, 2022) from this dependence, because thermal, nuclear and hydroelectric systems directly depend on water availability.	1	International Recommendations for Energy Statistics: https://unstats.un.org/unsd/energystats/methodology/documents/IRESweb.pdf
Proportion of population without quality access to electricity	B S; E n	A relevant indicator, but internationally it still needs to be defined what "quality access" means from a methodological and measurement point of view.	3	For example, Spain's Red Eléctrica measures "non-availability rate" (percentage of total time)

Proportion of world heritage sites without an emergency preparedness plan	C H	Countries have the duty to supervise and approve emergency preparedness plans; see also UNESCO database: https://whc.unesco.org/en/list/	2	UNESCO: Emergency preparedness plans: https://whc.unesco.org/archive/2007/whc07-31com-72e.pdf
Proportion of land that is degraded over total land area (SDG 15.3.1)	E c; F; W; E n; H e; C H	Possible proxy indicator: Change of land area affected by soil erosion (global CC set indicator 61); this is an indicator that can also be used to measure impact	1	SDG and CC
Coping capacity				
Proportion of agricultural area under productive and sustainable agriculture (SDG 2.4.1)	E c; F		2	SDG and CC
International Health Regulations (IHR) capacity and health emergency preparedness (SDG 3.d.1)	P; H e		1	SDG
Number of people per 100,000 that are covered by early warning information through local governments or through national dissemination mechanisms (SF G-3)	P		2	SF
Percentage of population exposed to or at risk from disasters protected through pre-emptive evacuation	P		2	SF

following early warning (SF G-6)				
Proportion of the target population covered by all vaccines included in their national programme (SDG 3.b.1)	P; H e		1	SDG
Health worker density (SDG 3.c.1)	P; H e		1	SDG
Proportion of population served by municipal waste collection	P; H; B S; C I; E A; E c; F; W; E n; H e; C H	This is a proxy indicator for a well-functioning society. It may or may not related to disasters specifically.	2	CC
Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type (SDG 15.1.2)	E c; F; W; E n; H e; C H		1	SDG and CC
Proportion of population using (a) safely managed sanitation services and (b) a hand-washing facility with soap and water (SDG 6.2.1)	P; B S; C I; F; W; H e; C H		1 (a) / 2 (b)	SDG and CC
Proportion of population with access to electricity (SDG 7.1.1)	P; B S; C I; E n		1	SDG
Percentage of local governments	P		2	SF

having a plan to act on early warnings (SF G-4)				
Proportion of government expenditure in strategic reserves	E A; G	National security plans usually define the strategic reserves; it is generally defined as the reserves of commodities or items that are held back from normal use by governments in pursuance of a particular strategy or to cope with unexpected events. Metadata should define what strategic reserves includes, and sectoral disaggregation is recommended. May not be comparable internationally.	2	
Direct impacts				
Number of disasters (per hazard type) declared by government per year	P; H; B S; C I; E A; E c; F; W; E n; H e; C H; G		1	Count numbers of declarations
Direct economic loss attributed to disasters in relation to global gross domestic product (GDP) (SDG 1.5.2, SF C1))	H; B S; C I; E A; E c; F; W; E n; H e; C H; G		1	SDG and SF
Proportion of government expenditure in disaster assistance in relation to GDP	G	Measures the impact on governance; it could be complemented with expenditure from non- government actors like NGOs, international agencies, foreign governments.	3	Data owned by government
Number of deaths attributed to disasters, per 100,000 population (SF A-2)	P	Sub-indicator of SDG 11.5.1	1	SDG and SF
Number of missing persons attributed to disasters, per	P	Sub-indicator of SDG indicator 11.5.1	1	SDG and SF

100,000 population (SF A-3)				
Number of injured or ill people attributed to disasters, per 100,000 population (SF B 2)	P		1	SF
Number of refugees, migrants and persons displaced by disasters, per 100,000 population	P	Broader scope than indicator 43 of global CC indicator set (referring to climate refugees); Internal Displacement Monitoring Centre (IDMC) has verified, consolidated and multi-sourced estimates of the number of people internally displaced or at risk of becoming displaced by conflict, violence, disasters and development projects across the world; database: https://www.internal-displacement.org/database/displacement-data ; A set of displacement indicators for DRR is currently being developed by IOM (https://environmentalmigration.iom.int/sites/g/files/tmzbd1411/files/documents/IOM-IDMC-%20Disaster%20Displacement%20Indicators%20-%20Version%20for%20comments.pdf)	2	IDMC: https://www.internaldisplacement.org/database/methodology CC
Proportion of destroyed dwellings in relation to total number of dwellings	H		1	Countries and insurance companies are counting this as absolute numbers:
Number of people whose destroyed dwellings were attributed to disasters (SF B-4)	P; H	It is recommended that this Sendai Framework indicator is presented as relative figure (per 100,000 population)	2	SF

Economic value of lost or damaged housing stock in relation to total value of housing stock	H		1	Countries and insurance companies are counting this as absolute number
Number of disruptions to basic services attributed to disasters (SF D-5)	H; B S	For the SF indicator it is proposed to include the following public services: Educational facilities, healthcare facilities, power/energy system, sewerage system, solid waste management, transport system, water supply, ICT system and emergency response	2	SF
Number of person days without electricity due to hazardous events	H; B S; E n; G	Allows for better international comparability than Sendai Framework Indicator D-5, therefore recommended core indicator	1	Service providers have this data available
Number of person days without gas supply due to hazardous events	H; B S; E n	Allows for better international comparability than Sendai Framework Indicator D-5, therefore recommended core indicator	1	Service providers have this data available
Number of person days without water supply due to hazardous events	H; B S; W; G	Allows for better international comparability than Sendai Framework Indicator D-5, therefore recommended core indicator	1	Service providers have this data available
Damage to critical infrastructure attributed to disasters (SF D-1)	B S; C I; G	Measurement unit: Index of Critical Infrastructure Damage = number of infrastructure units and facilities damaged/population * 100,000	2	SF
Proportion of land that is degraded over total land area (SDG 15.3.1)	E C; F; W; H e; C H	Possible proxy indicator: Change of land area affected by soil erosion (global CC set indicator 61); ideally, land degradation caused by hazardous events is presented separately.	1	SDG and CC

Direct economic loss to cultural heritage damaged or destroyed attributed to disasters (SF C-6)	C H		2	SF and CC
Proportion of flooded land	P; H; B S; C I; E A; E c; F; W; E n; H e; C H		1	Flooded land information usually available
Proportion of forest area affected by forest fires	F; E n; H e; C H		1	CC
Direct agricultural loss attributed to disasters (SF C-2)	E c		2	SF and CC

9.9 Annex references

Al-Yaari, A., Zhao, Y., Cheruy, F., & Thiery, W. (2023): Heatwave characteristics in the recent climate and at different global warming levels: A multimodel analysis at the global scale. *Earth's Future*, 11(9), e2022EF003301.

Bondesanf, M., Castiglioni, G.B., Elmis, C., Gabbianellis, G., Marocco, R., Pirazzolift, P.A. and Tomasin, A., 1995. Coastal areas at risk from storm surges and sea-level rise in northeastern Italy. *Journal of Coastal Research*, pp.1354–1379.: https://www.researchgate.net/profile/Fabrizio-Antonioli/publication/312289623_Sea-level_rise_and_potential_drowning_of_the_Italian_coastal_plains_Flooding_risk_scenarios_for_2100/links/5e044b0e299bf10bc37973ab/Sea-level-rise-and-potential-drowning-of-the-Italian-coastal-plains-Flooding-risk-scenarios-for-2100.pdf

Climate ADAPR (2025): Tropical Nights. <https://climate-adapt.eea.europa.eu/en/metadata/indicators/tropical-nights> (18.03.25).

Climate Change Initiative Coastal Sea Level Team (2020): Coastal Sea level anomalies and associated trends from Jason satellite altimetry over 2002-2018. *Sci Data*, 7(1):357, doi: 10.1038/s41597-020-00694-w, PMID: 33082349; PMCID: PMC7576834.

Climate Data Guide (2025): Standardized Precipitation Evapotranspiration Index (SPEI). <https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-evapotranspiration-index-spei> (18.03.25).

Climate Data Store (2025): Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections. <https://cds.climate.copernicus.eu/datasets/sis-extreme-indices-cmip6?tab=overview> (19.03.25).

Climpact (2025): Indices. <https://climpact-sci.org/indices/#index-TNIt2> (18.03.25).

ETCCDI (2025): Climate Change Indices. https://etccdi.pacificclimate.org/list_27_indices.shtml (18.03.25).

Ganguli, P., & Merz, B. (2019): Extreme coastal water levels exacerbate fluvial flood hazards in Northwestern Europe. *Scientific reports*, 9(1), 13165.

Handbook of Extreme Heat Indicators and Indices; A Measurement Guide for Characterising and Monitoring Heatwaves for Impact Services - Advanced Draft for External Review

Herold, N., Ekström, M., Kala, J., Goldie, J., & Evans, J. P. (2018): Australian climate extremes in the 21st century according to a regional climate model ensemble: Implications for health and agriculture. *Weather and climate extremes*, 20, 54-68.

Kim, D. W., Deo, R. C., Lee, J. S., & Yeom, J. M. (2017): Mapping heatwave vulnerability in Korea. *Natural Hazards*, 89, 35-55.

Khan, A., Papazoglou, E. G., Cartalis, C., Philippopoulos, K., Vasilakopoulou, K., & Santamouris, M. (2022): On the mitigation potential and urban climate impact of increased green infrastructures in a coastal mediterranean city. *Building and Environment*, 221, 109264.

Kouman, K. D., Kabo-bah, A. T., Kouadio, B. H., & Akpoti, K. (2022): Spatio-temporal trends of precipitation and temperature extremes across the North-East Region of Cote d'Ivoire over the period 1981–2020. *Climate*, 10(5), 74.

Leander, R., Buishand, T. A., & Tank, A. K. (2014): An alternative index for the contribution of precipitation on very wet days to the total precipitation. *Journal of climate*, 27(4), 1365-1378.

Li, B., Zhou, W., Zhao, Y., Ju, Q., Yu, Z., Liang, Z., & Acharya, K. (2015): Using the SPEI to assess recent climate change in the Yarlung Zangbo River Basin, South Tibet. *Water*, 7(10), 5474-5486.

Li, C., Gu, X., Bai, W., Slater, L. J., Li, J., Kong, D., ... & Li, Y. (2021): Asymmetric response of short-and long-duration dry spells to warming during the warm-rain season over Eastern monsoon China. *Journal of Hydrology*, 603, 127114.

Li, J., Huo, R., Chen, H., Zhao, Y., & Zhao, T. (2021): Comparative assessment and future prediction using CMIP6 and CMIP5 for annual precipitation and extreme precipitation simulation. *Frontiers in Earth Science*, 9, 687976.

Lima, D. C., Lemos, G., Bento, V. A., Nogueira, M., & Soares, P. M. (2023): A multi-variable constrained ensemble of regional climate projections under multi-scenarios for Portugal–Part I: An overview of impacts on means and extremes. *Climate Services*, 30, 100351.

Lee, T. L. (2006): Neural network prediction of a storm surge. *Ocean Engineering*, 33(3-4), 483-494.

Lu, C., Ying Sun, & Xuebin Zhang (2018): Multimodel detection and attribution of changes in warm and cold spell durations. *Environmental Research Letters*, 13(7), 074013.

Luther, N., et al. Non-parametric indicators for climate and climate impact applications. in preparation.

Murray, Virginia; Abrahams, Jonathan; Abdallah, Chadi; Ahmed, Kanza; Angeles, Lucille; Benouar, Djillali; Brenes Torres, Alonso; Chang Hun, Choe; Cox, Simon; Douris, Jim; Fagan, Lucy; Fra Paleo, Urbano; Han, Qunli; Handmer, John; Hodson, Simon; Khim, Wirya; Mayner, Lidia; Moody, Nick; Moraes, Luiz Leal ; Osvaldo; Nagy, Michael; Norris, James; Peduzzi, Pascal; Perwaiz, Aslam; Peters, Katie; Radisch, Jack; Reichstein, Markus; Schneider, John; Smith, Adam; Souch, Claire; Stevance Anne-Sophie; Triyanti, Annisa; Weir, Maddie; Wright, Natalie (2021): Hazard Information Profiles: Supplement to UNDRR-ISC Hazard Definition & Classification Review: Technical Report: Geneva, Switzerland, United Nations Office for Disaster Risk Reduction; Paris, France, International Science Council. DOI: 10.24948/2021.05.

Nairn, J.R. & Fawcett, R.G. (2013): Defining heatwaves: heatwave defined as a heat-impact event servicing all community and business sectors in Australia, Centre for Australian Weather and Climate Research Technical Report #60. Download (PDF from [cawcr.gov.au](https://www.cawcr.gov.au)): https://www.cawcr.gov.au/technical-reports/CTR_060.pdf.

NASA (2025): Standardized Precipitation Index (SPI). <https://gmao.gsfc.nasa.gov/research/subseasonal/atlas/SPI-html/SPI-description.html> (18.03.25).

Oikonomou, C., Flocas, H. A., Hatzaki, M., Nisantzi, A., & Asimakopoulos, D. N. (2010): Relationship of extreme dry spells in Eastern Mediterranean with large-scale circulation. *Theoretical and applied climatology*, 100, 137-151.

Perkins, S.E. & Alexander, L.V. (2013): On the Measurement of heatwaves, *J. Climate*, 26, 4500–17. doi: 10.1175/JCLI-D-12-00383.1

Reddy, Nagireddy Masthan, & Subbarayan, Saravanan (2023): Extreme precipitation indices over India using CMIP6: a special emphasis on the SSP585 scenario. *Environmental Science and Pollution Research*, 30(16), 47119-47143.

Saha, A., Patil, M., Goyal, V. C., & Rathore, D. S. (2018): Assessment and impact of soil moisture index in agricultural drought estimation using remote sensing and GIS techniques. In *Proceedings* (Vol. 7, No. 1, p. 2). MDPI.

Saumya, Singh & Mall, R. K. (2023): Frequency dominates intensity of future heat waves over India. *Iscience*, 26(11).

Uni-Hamburg (2023): Climate Indices of Air Temperature. <https://www.cen.uni-hamburg.de/en/icdc/data/climate-indices/climate-indices-of-temperature-and-precipitation/climate-indices-of-air-temperature.html> (18.03.25).

United Nations Economic Commission for Europe (2025). *Set of Core Disaster-Risk-Related Indicators: White Cover Version (March 2025)*. Geneva: UNECE.

Valverde, Maria C., & Marengo, José A. (2014): Extreme rainfall indices in the hydrographic basins of Brazil. *Open Journal of Modern Hydrology*, 2014.

Villa-Falfán, C., Valdés-Rodríguez, O. A., Vázquez-Aguirre, J. L., & Salas-Martínez, F. (2023): Climate indices and their impact on maize yield in Veracruz, Mexico. *Atmosphere*, 14(5), 778.

Wang, X., Hou, X., & Zhao, Y. (2021): Changes in consecutive dry/wet days and their relationships with local and remote climate drivers in the coastal area of China. *Atmospheric Research*, 247, 105138.

WMO (2012): Standardized Precipitation Index User Guide (7 bis, avenue de la Paix — P.O. Box 2300 — CH 1211 Geneva 2 — Switzerland). <https://library.wmo.int/records/item/39629-standardized-precipitation-index-user-guide>.

Xiang-Ling, T., Xin, L., & Yanwei, Z. (2020): Estimation of future extreme precipitation changes in Xinjiang based on RegCM4. 4 simulations. *Natural Hazards*, 102(1), 201-218.

Xoplaki, E., Ellsäßer, F., Grieger, J., Nissen, K.M., Pinto, J.G., Augenstein, M., Chen, T.-C., Feldmann, H., Friederichs, P., Gliksman, G., Goulier, L., Haustein, H., Heinke, J., Jach, L., Knutzen, F., Kollet, S., Luterbacher, J., Luther, N., Mohr, S., Mundersbach, C., Müller, C., Rousi, E., Simon, F., Suarez-Gutierrez, L., Szemkus, S., Vallejo-Bernal, S.M., Vlachopoulos, O., & Wolf, F. (2025): Compound events in Germany in 2018: drivers and case studies. *Natural Hazards and Earth System Sciences* 25, <https://doi.org/10.5194/nhess-25-541-2025>

Zampieri, M., Ceglar, A., Dentener, F., & Toreti, A. (2017): Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environmental Research Letters*, 12(6), 064008.

Zare, S., Hasheminejad, N., Shirvan, H. E., Hemmatjo, R., Sarebanzadeh, K., & Ahmadi, S. (2018): Comparing Universal Thermal Climate Index (UTCI) with selected thermal indices/environmental parameters during 12 months of the year. *Weather and climate extremes*, 19, 49-57.

Zarrin, Azar & Dadashi-Roudbari, Abbasali (2022): Spatiotemporal variability, trend, and change-point of precipitation extremes and their contribution to the total precipitation in Iran. *Pure and Applied Geophysics*, 179(8), 2923-2944.