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VALIDATED LOCAL RISK ACTIONABLE DATA FOR ADAPTATION



D4.4

Final data downscaling description

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1. Executive summary

1.1 Description of the deliverable content and objectives

The scope of this deliverable covers guidance on selecting climate data for adaptation and planning challenges such as urban heat islands, water stress, coastal and soil erosion, heavy rainfall and flash floods, and wildfires—use cases that reflect the types of questions and decisions the VALORADA tools are designed to support. The deliverable aims to support cities and local stakeholders in understanding the interpretation and use of available Earth Observation (EO) and climate data for climate risk assessment and adaptation planning. The primary focus is on the process of integrating climate and EO information, and what added value this integration can bring.
The document provides:

- A practical overview of climate data sources available through the Copernicus Climate Data Store and explains the importance of spatial and temporal resolution when using climate projections for local decision-making.
- An introduction to downscaling methods, including dynamical, statistical, and hybrid approaches, with concrete examples of their application to key climate risks. Downscaling refers to the process of transferring coarse-resolution general circulation model output to a finer spatial scale, making it more meaningful for analyzing local and regional climate conditions.
- A discussion of what cities can realistically expect from downscaled climate data, including both benefits and limitations.
- Guidelines for selecting appropriate climate data on intended use cases, emphasizing the importance of considering uncertainty, model spread, and scenario diversity. These guidelines support municipalities, companies, and researchers in overcoming current barriers to integrating climate and EO data. In this context, EO data can complement in-situ observations and reanalysis by providing high-resolution, independent measurements with growing long-term coverage, offering clear potential for downscaling in data-sparse regions. Unlocking this potential will require overcoming challenges in preprocessing, variable compatibility, and temporal coverage through harmonized datasets and improved modelling techniques.
- An overview of tools and resources to support cities in visualizing and communicating climate data and uncertainties.

1.2 Deviation from objectives, corrective action (if applicable)

The original scope of the deliverable was to provide a set of downscaled climate data. However, at the beginning of the project, the Climate Data Store (CDS) from ECMWF released a set of high-resolution climate indicators with a spatial resolution of approximately 1 km. These datasets have been utilized to develop the tools described in Deliverable D4.5. As a result, based on the discussions at the General Assembly, the project shifted from generating new downscaled data to leveraging these existing high-resolution indicators to support tool development. By doing so, VALORADA has focused on providing a useful guidance regarding the advantages and disadvantages of various downscaling techniques, particularly in the context of climate adaptation and planning. This guidance aims to support stakeholders in selecting appropriate methods based on their specific needs, resources, and decision-making contexts.

1.3 Major outcome

Here, we provide guidance on using and interpreting available climate data. In addition, we offer advice on how climate data could be downscaled, provided that, for example, the necessary observational data are available. The key takeaways are:

- Downscaling improves local climate risk information but cannot eliminate uncertainty.
- The choice of method, resolution, and models should be matched to the use case, accuracy requirements, and available reference data.

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- Multiple models and scenarios should be used, and model skill should be checked against observed climate.
- Data should be interpreted together with climate experts to avoid misuse.

2. Introduction

2.1 About VALORADA

The EU aims to transform 150 European regions into sustainable and climate resilient regions by 2030. VALORADA contributes to addressing this challenge by co-developing tested FAIR customisable data-manipulation tools to access available climate datasets and to enable the sharing, community validation and use of local socioeconomic, demographic and Earth-Observation data. With a rigorous transdisciplinary approach, the respective risks of climate change are analysed with the local actors in five demonstrators in Europe. Data required for the analysis are compiled from the various already existing repositories (e.g., Copernicus Climate Change Climate Data Store) and locally sourced non-climate data catalogues processed by local communities and regions. The project will co-develop and make available prototype climate data and non-climate data manipulation tools to support and improve existing data portals and platforms and to enable user-oriented multi-data integration.

VALORADA aims to achieve Technology Readiness Levels (TRL) 7 and above. VALORADA's tools will enable the acquisition of different useful climate and non-climate data and make them "interoperable" in terms of metadata, as well as tools able to harmonise the geographical and time references chosen for the data. The "Analyst toolbox" will be composed of software tools able to combine different kinds of data all relevant for assessing climate risks and to calculate resulting indicators. VALORADA will contribute to scaling up to 150 regions through the implementation of dedicated scalability and replicability activities with at least 10 European regions and through strong collaboration with other Horizon projects. Additional activities include capacity-building schemes for end users as well as providers of climate services. VALORADA will explore and assess the options to facilitate the connection of the VALORADA data tools to the Copernicus Atmosphere Data Store.

VALORADA's vision statement: VALORADA wants to empower European regions and cities to steer the upcoming societal transformation towards sustainable and climate-resilient development through their own actions.
VALORADA's mission statement: VALORADA will enable the integration of diverse datasets that enable merging local knowledge with climate and non-climate datasets by means of co-developed data-manipulation tools and climate data.

2.2 Objectives of WP4

• Define and develop multi-source data manipulation tools and make them available and customised to the service providers in charge of the regional demonstrators.

• Define together with WP1, WP2 and with the service providers of WP3, the climate service data which needs specific geographic downscaling, and perform the needed downscaling for the benefit of each service provider of WP3.

• Develop tools for generating a set of indicators combining climate, EO-based and non-climate data for assessing the vulnerability and risks mitigation benefits of the regions

• Assess the maturity level for operationalization with full compliance of the FAIR principles

• Assess the potential integration of the relevant tools into the Climate and Atmosphere Data Store (CADS) and/or other C3S related activities and Climate-ADAPT.

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All the tools developed in this WP4 will comply with findability, accessibility, interoperability and reusability as described within the FAIR data principles.

2.3 Objectives of Task 4.2

Definition of Task 4.2: Climate data downscaling

This task will perform the appropriate geographical downscaling of the climate and atmosphere historical and projection data to resolutions needed for some applications of the project demonstrators, specifically in urban environments, by using existing techniques and algorithms (based on statistical methods and machine learning) already used by FMI. EURO-CORDEX data, which is already available at a fairly good resolution (0.11x0.11°), including hindcast, present-day, and future projections based on three different forcing scenarios, is one specific option to be used as climate data input. The used downscaling methods will be potentially adapted to the specific environments and needs. The downscaled data will also include a "scoring" for assessing the uncertainty attached to the downscaling procedure, depending on the available additional observation data. The downscaling will be performed on FMI's own processing platform, applied onto the geographic areas of interest as defined by the local service providers (mostly the urban areas part of the demonstrators), and the results will be made available to be further used by the local service providers. The downscaled data will be stored either on FMI's own FAIR data repository METIS, on the platforms of the demonstrators, on TerraNIS' own servers, depending on data storage availability.

3. Climate Data, Downscaling and Their Role in Climate Risk Assessment

3.1 Climate data in VALORADA

In VALORADA, Climate Impact Chains (CICs) have been developed to characterize local climate risks for each demonstrator region in Task 1.1, and in Task 1.3 these CICs have been used to select and define relevant climate indicators (Deliverable 1.3 "Selected climate risk indicators with detailed computing metrics"). In Task 4.1 (Deliverable 4.5 "Initial definition and description of climate risks indicators implementation"), tools have been developed to calculate and visualize these indicators using local databases, climate data, and information from Earth Observation and land use data. Note on terminology: Climate variables provide general climate information (e.g., temperature or precipitation). Climate risk indicators, on the other hand, are tailored metrics derived from these variables that translate climate information into decision-relevant measures of risk, such as heat stress, or flash flood potential.

When using climate data in the calculation of indicators, it is essential to be able to assess the relationships between the indicators and the underlying climate variables. A key challenge, even when such relationships are known, is whether suitable modelling approaches are available to project indicator developments based on projected climate change. At the time of writing this report, no comprehensive indicator-specific assessment has yet been carried out to determine what can be modelled in this way. For this reason, at present only the indicators related to irrigation water demand integrate climate data directly into their calculations. For the other indicators, the VALORADA climate dashboard produced in Task 4.1 currently presents relevant climate data alongside the risk indicator values (see Table 1 for details) to illustrate the evolution of climate variables that can influence the indicator values. A complementary GeoNetwork catalogue developed also in Task 4.1 compiles all indicators and datasets displayed on the dashboards.

For each demonstrator region, specific climate dashboards (an example in Section 4.3) allow to visualise a selection of climate variables from the Climate indicators for Europe from 1940 to 2100 dataset (ECDE, Section 3.3.3), with the selected variables listed in Table 1. This dataset combines reanalysis data for the historical period with multi-model climate projections for the future. The historical part is based on the ERA5 reanalysis, while future projections use an ensemble of EURO-CORDEX regional climate model simulations driven by CMIP5 global climate models under different emission scenarios (RCPs). Statistical bias adjustment methods are applied to

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harmonise reanalysis and model data, allowing the calculation of consistent climate indicators such as temperature and precipitation extremes across the full 1940–2100 period.

Table 1. VALORADA dashboards' selected Climate risk indicators and supporting climate variables from the European Climate Data Explorer, ECDE. Data source: Climate indicators for Europe from 1940 to 2100 derived from reanalysis and climate projections https://cds.climate.copernicus.eu/datasets/sis-ecde-climate-indicators.

Risk Indicator Name \ Climate variables for indicators (Source ECDE)	Number of house-holds affected by drought	Flood-related indicators	Increase in soil degradation and desertification	Number of hectares of productive land lost to soil erosion	Share of mixed forest of all forests and general tree composition of forests	Total forest area impacted by wildfire per year	Percentage of coastline under marine protection	Share of forested area	Population vulnerability to heat waves and sub-indicators
Tropical Nights									X
Hot Days						X			X
Climatological Heatwave Days						X			X
Extreme Precipitation Total		X	X	X					
Extreme Precipitation Days		X	X	X					
Flood Recurrence		X							
Meteorological Droughts Duration	X		X	X					
Meteorological Droughts Magnitude	X		X	X					
Extreme Wind Speed Days			X	X	X	X		X	
Relative Sea Level Rise							X		
Extreme Sea Level							X		
High Fire Danger Days					X	X		X	
Fire Weather Index					X	X		X	

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3.2 Downscaling Framework

Reliable climate data and a clear understanding of its uncertainties (see, e.g., Annex 1 for Key Sources of Uncertainty in Climate Projections) are essential for high-quality assessments of climate change impacts. While Global Climate Models (GCMs) offer valuable projections of future climate, their coarse resolution—typically 100 to 250 km—limits their usefulness for local-scale decision-making. To address this, downscaling techniques are used to convert large-scale model outputs into higher-resolution, localized data. Downscaling methods were described in Del 4.3 (available at https://grandearmeeconseil.sharepoint.com/:b:/r/sites/valorada-project/Documents%20partages/General/WP6/Deliverables/D4.3/VALORADA_D4.3_final.pdf?csf=1&web=1&e=kFblZZ). In this current Deliverable 4.4, the dynamical and statistical downscaling (e.g., Benestad, 2016 and Maraun & Widmann, 2018) are briefly described in Annexes 2 and 3. In addition, an overview of available free statistical downscaling tools is given in Annex 4. Note, that recent machine learning methods can be considered an extension of the statistical downscaling. Rampal et al. (2024) provide an up-to-date overview of machine learning methods.

High-resolution reference data for local conditions are needed. Many widely available downscaled products, such as the bioclimatic indicators mentioned below, take only into account the relationship between orography and a climate state variable. But, especially for statistical downscaling, long time series of local-scale observations, referable independent from the reanalyses, would be useful, but such time series can be hard to find. Moreover, users should be aware that different climate variables are measured and reported in distinct ways. For example, although temperature and precipitation are now commonly recorded in real time, historical records often show precipitation data aggregated and reported only once a day, which can result in the loss of sub-daily variability. This can lead to an underestimation of extreme precipitation events.

3.2.1 Which Variables Benefit Most from Downscaling?

Variables such as temperature and precipitation may show significant improvements with downscaling, temperature more than precipitation (e.g., Gutiérrez et al. 2019). Downscaling of variables beyond temperature and precipitation tends to be more demanding in terms of model complexity, input data requirements, and validation needs (e.g., Wilby and Dawson, 2013). The achievable skill improvement is therefore more dependent on the availability of high-quality local observations and the suitability of the chosen downscaling method.

3.2.2 What Cities Can Realistically Expect from Downscaled Climate Data

3.2.2.1 Benefits

High-quality downscaled climate data can offer valuable improvements for urban-scale planning and decision-making. One of the key benefits is better local tailoring: high-resolution data can reflect local conditions such as topography, coastline effects, or urban heat islands more accurately than coarse-resolution global models. This improves the relevance of climate indicators for local impact assessments.

Another important benefit emerges when data providers also offer clear visualizations and accessible formats. When high-resolution climate information is presented in an understandable, visually engaging, and easy-to-use way—such as maps, interactive dashboards, or ready-to-use indicators—it is much more likely to reach decision-makers, inform policy discussions, and be integrated into urban planning processes. In such cases, the added value of downscaling is not just in the scientific precision but in the practical uptake and application of the information.

3.2.2.2 Limitations

While downscaling adds value, it also comes with limitations that cities should be aware of. First, downscaled data cannot exceed the quality of the original climate model data—uncertainties in emissions, model structure, and natural variability remain (IPCC, 2021, Chapter 4.2). Second, city-scale future land use and urban

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development are usually not included in climate model projections, meaning that city-specific changes (e.g., densification, greening) are not reflected unless explicitly modelled (e.g. Daniel et al. 2019; McManamay et al. 2024). Third, uncertainty remains throughout the modelling chain: downscaling reduces certain biases or adds detail, but it does not eliminate the fundamental uncertainties in future climate projections (e.g., Gutiérrez et al. 2019). In addition, the reliability of downscaled data depends heavily on the availability of local observations. Without sufficient local measurement data—such as weather station records or urban monitoring—statistical downscaling cannot be properly calibrated, and validation of either statistical or dynamical methods becomes challenging. This may reduce confidence in the results, especially in regions with sparse observation networks.

There is no single best downscaling method suitable for all applications and regions. While some methods may perform better for specific purposes, each method involves assumptions that need to be carefully evaluated. Users may select a downscaling approach that aligns with their specific information needs—such as the desired spatial and temporal resolution—as well as their available resources, including data, expertise, computing capacity, and time frames.

3.2.2.3 Key questions to ask the data provider

To support informed use of downscaled climate data, cities can ask data providers key questions to better understand the data's origins and limitations. We suggest the following check list:

- What climate models and emissions scenarios were used, and how were they selected?
- Was an ensemble of models used, and are the results expressed as ranges or probabilities to reflect uncertainty?
- What downscaling method was applied (statistical, dynamical, hybrid), and what is its resolution and known limitations?
- How are uncertainties presented or communicated—are there indicators of model spread, scenario differences, or confidence levels?
- Does the data include local land use assumptions or urban features, or is it based on regional-scale information only?

By understanding the assumptions and limits behind the data, cities can use it more effectively and responsibly in climate risk assessments and adaptation planning.

3.3 Climate Data already available

There are many portals that provide climate data from research institutes, national meteorological and hydrological institutes, and government agencies. Some are open and free, while others have more restrictive licences. While some of the available data is 'raw', based on unprocessed model outputs, there are also ready-to-use downscaled climatic and bioclimatic indicators, albeit with some caveats. Here, we focus on the open-access data provided by Copernicus Climate Change Service (C3S) repositories.

3.3.1 The Copernicus Climate Data Store

The Climate Data Store (CDS, https://cds.climate.copernicus.eu/) is a comprehensive repository offering open access to a diverse array of climate data and model outputs. It provides valuable resources for climate research, policy-making, and strategic planning by delivering high-quality data from global (CMIP) and regional climate models (e.g. EURO-CORDEX data). The CDS also houses reanalysis datasets (e.g., ERA5 and ERA5-Land data sets), which are historical climate reconstructions that blend observational data with model outputs to create consistent time series of past weather and climate conditions. Complementing these are satellite observations that capture a range of atmospheric, oceanic, and land surface parameters, as well as in-situ measurements from ground-based monitoring networks. The CDS offers a user-friendly interface for easy access to this data, along with tools for data visualization and processing. There are useful graphical user interfaces that facilitate easy access to CDS data. For example, climate projections, reanalyses and observations can be browsed with Copernicus Interactive Climate Atlas (https://atlas.climate.copernicus.eu/atlas), see Figure 1.

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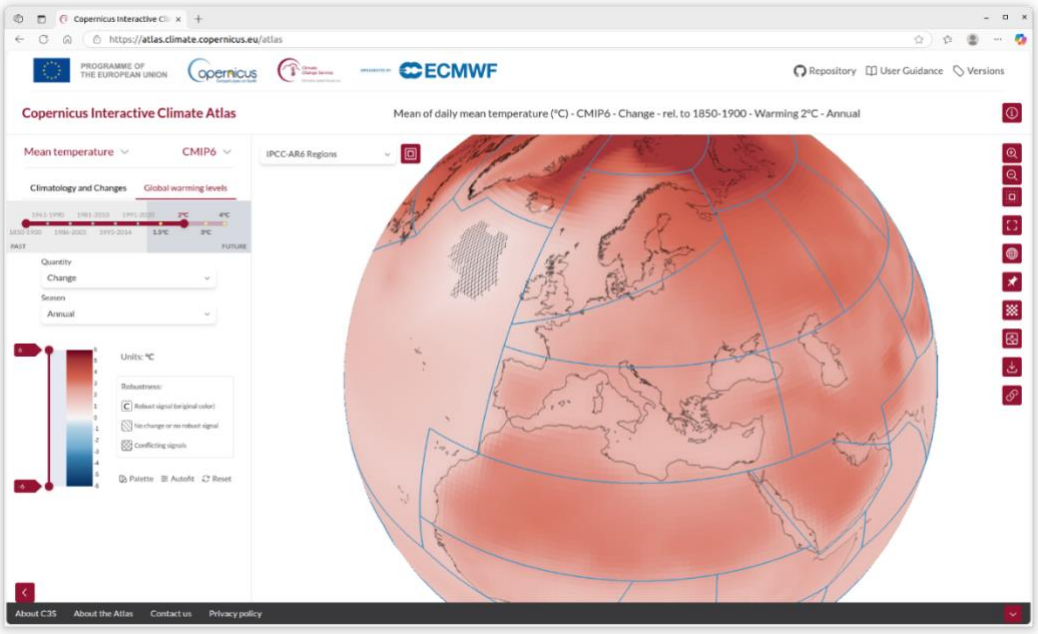


Figure 1. Screenshot of the Copernicus Interactive Climate Atlas, https://atlas.climate.copernicus.eu/atlas.

3.3.2 Bioclimatic Indicators Data

Bioclimatic indicators, already downscaled to 1 x 1km, can be downloaded (https://cds.climate.copernicus.eu/datasets?q=bioclimatic). The indicators are calculated based on daily CMIP5 climate projections from 10 Global Circulation Models for two future climate scenarios, Representative Concentration Pathway (RCP) 4.5 & RCP 8.5. Statistics available from the models are mean, median, 25th quartile and 75th quartile. However. only annual values of 20-year average are available for the scenarios. This can be too coarse for many projects and custom downscaling might be needed. According to validation reported, global temperature trends have low uncertainty and comparisons between CMIP5 and ERA5 indicators show good agreement for temperature trends and hot and cold extremes (e.g., summer and frost days). Other indicators such as cloud cover, precipitation variability and the associated trends in drought and dryness parameters have higher uncertainties. Especially soil moisture has large uncertainties due to sparse observations. Bias adjustments against ERA5 can reduce some biases, but future trends remain uncertain and model dependent. Users should compare indicators with observational trends and consider model spreads to address uncertainties. (Users guide, section 2.4.7: https://dast.copernicus-climate.eu/documents/sis-biodiversity/C3S_D427.3.1.1_Product_user_guide-Bioclimatic_indicators_CMIP5-1km_v2.3.pdf)

3.3.3 European Climate Data Explorer

The 30 climate impact indicators, which are calculated from the CDS data and based on the needs identified by adaptation users via the European Environment Agency (EEA), can be browsed using the European Climate Data Explorer (ECDE, https://apps.copernicus-climate.eu/c3s-apps/ecde/) or downloaded from https://cds.climate.copernicus.eu/datasets/sis-ecde-climate-indicators. They provide multi-model results and are aggregated at Nomenclature of Territorial Units for Statistics (NUTS) regions with defined and standardised reference periods. The validation of indicators has primarily been conducted by comparing the output with existing indicators available on the ECDE or other publications from the EEA, where the same indicators were presented using different input data (user guide section 2.4.5). Although it wasn't always possible to verify against an identical numerical dataset, it was possible to confirm that the indicators are consistent with other publications.

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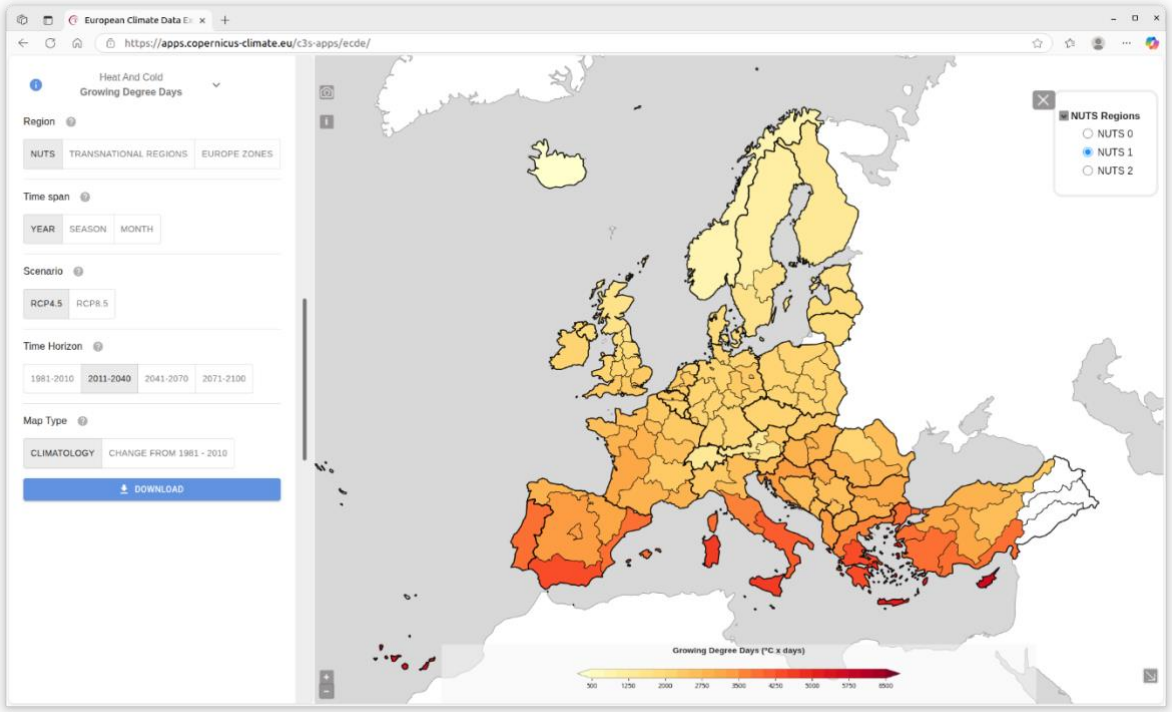


Figure 2. Screenshot of the European Climate Data Explorer (ECDE, https://apps.copernicus-climate.eu/c3s-apps/ecde/).

Selected climate indicators of this ECDE dataset are being visualized in the VALORADA dashboards alongside other indicator values (see Table 1 for details), enabling direct comparison and supporting climate risk assessments.

3.4 Example Applications to Climate Risks

Table 2 provides an overview of which downscaling approaches and models are commonly applied to different types of climate risks, including urban heat, extreme precipitation, flooding, coastal and soil erosion, wildfire, and drought. The following subsections (3.4.1–3.4.3) present selected examples in more detail.

Table 2. Overview of downscaling approaches and models applied to different climate risks (based on text in Sections 3.4.1–3.4.3). Abbreviations: GCM = Global Climate Model; RCM = Regional Climate Model; CPM = Convection-Permitting Model; UHI = Urban Heat Island; GEV = Generalized Extreme Value (statistical distribution for modelling extremes); IDF = Intensity–Duration–Frequency; SPI = Standardized Precipitation Index; SPEI = Standardized Precipitation–Evapotranspiration Index; FWI = Fire Weather Index.

Climate risk	Main approaches	Typical models/tools	Purpose/output
Urban heat island (UHI), urban heat stress	Dynamical, Statistical, Combined	Urban canopy models (TERRA-URB, SURFEX) coupled with RCMs/CPMs; statistical bias correction (e.g., quantile mapping, GEV)	Represent intra-urban temperature variability; assess future UHI intensity and heat stress
Extreme precipitation	Dynamical + Statistical	CPMs (1–3 km resolution); bias correction (quantile mapping, GEV fitting)	High-resolution rainfall; estimation of return periods and IDF curves

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Flood hazards	Dynamical	RCM/CPM precipitation forcing for hydrological models	Flood risk mapping; peak discharge estimation
Coastal erosion & storm surges	Dynamical	Atmosphere–ocean–wave modelling chains downscaled from GCMs/RCMs	Coastal risk assessment
Soil erosion	Dynamical	Downscaled rainfall forcing for erosion models (e.g., RUSLE, WEPP)	Soil erosion assessment
Wildfire risk	Statistical + Dynamical	Downscaled meteorological variables (temperature, humidity, wind, precipitation) → Fire Weather Index (FWI)	Fire risk assessment
Water stress & drought	Statistical + Hydrological	Downscaled precipitation and evapotranspiration → drought indices (SPI, SPEI); hydrological models	Drought assessment

3.4.1 Examples of Dynamical downscaling

Dynamical downscaling has been applied to various aspects of urban climate risk assessment, including the evaluation of urban heat islands (UHIs), extreme precipitation, flood hazards, and coastal and soil erosion. It is particularly valuable for representing extreme events, regions with complex topography or coastlines, and processes with strong spatial gradients. While regional climate models (RCMs) enhance the representation of regional climate processes, their standard resolution (typically 10–50 km) is often insufficient to resolve intra-urban variability.

To better capture urban-specific effects, additional modelling approaches such as urban canopy models are used. Urban canopy models (e.g., SURFEX, TERRA-URB) can be coupled with RCMs to simulate the influence of urban morphology and land use on local temperature and energy fluxes. These tools improve the representation of UHI effects in future climate scenarios. For example, Wouters et al. (2017) applied urban-enhanced dynamical downscaling using EURO-CORDEX data to assess heat stress in cities. In contexts where long observational records exist, statistical methods can also complement dynamical approaches by adjusting simulated urban temperatures.

Beyond urban environments, dynamical downscaling supports other climate risk assessments. Coastal erosion risk studies require high-resolution projections of wind, storm surges, and wave dynamics, which are typically obtained by downscaling GCM data through regional atmosphere–ocean–wave modelling chains. Soil erosion modelling, on the other hand, relies on downscaled rainfall data at daily or sub-daily resolution to drive empirical or process-based models such as RUSLE or WEPP.

Despite its strengths, the high computational cost of RCMs often limits the number of ensemble members, and their spatial resolution still requires further refinement or coupling with urban models for urban-scale applications.

3.4.2 Statistical Downscaling Examples

Statistical downscaling methods are widely used in urban climate risk assessments, where high spatial and temporal resolution is essential. For example, in extreme precipitation and flooding studies, high-resolution downscaling can improve the estimation of short, intense rainfall events—particularly when combined with convection-permitting models (CPMs) at 1–3 km resolution. Bias correction techniques such as quantile mapping and GEV fitting are then applied to adjust model outputs, enabling the estimation of return levels and intensity–duration–frequency (IDF) curves.

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Similar approaches are applied in wildfire risk assessments, where downscaled meteorological variables—temperature, humidity, wind, and precipitation—provide the necessary inputs for computing fire danger indices such as the Fire Weather Index. Water stress and drought projections likewise benefit from downscaled precipitation and evapotranspiration data, which feed into hydrological models to calculate drought indices like the Standardized Precipitation Index (SPI) or the Standardized Precipitation–Evapotranspiration Index (SPEI). This is particularly important in regions lacking high-resolution climate model data, as demonstrated by Spinoni et al. (2015).

3.4.3 A Combination of Dynamic and Statistical downscaling examples

Several recent studies have demonstrated the potential of this combined approach in regional and urban-scale climate applications. For instance, Burgstall et al. (2021) applied quantile mapping to statistically downscale an ensemble of EURO-CORDEX regional climate simulations. Their method corrected systematic biases in precipitation and temperature, resulting in improved accuracy for local-scale climate impact assessments.

A more integrated methodology was developed by Le Roy et al. (2021), who introduced a statistical–dynamical downscaling framework tailored for analyzing the urban heat island (UHI) effect. Using the EURO-CORDEX ensemble as input, the approach combined regional climate projections with urban canopy models and local observational corrections to assess changes in UHI intensity under climate change.

Similarly, Schoetter et al. (2020) proposed a statistical–dynamical downscaling method specifically for urban applications. Their technique involved nesting convection-permitting simulations within broader regional climate models and applying a statistical correction based on observed urban–rural temperature contrasts. This enabled more accurate estimation of present and future UHI effects across different urban morphologies.

3.5 EO data for downscaling

EO data are an attractive addition to in-situ observations and reanalyses, providing observations independent from the ground infrastructure. With a spatial resolution ranging from on the order of a kilometre (meteorological instruments, such as MODIS) to less than 10 metres (land cover instruments onboard, e.g., SPOT and SENTINEL-2) and with time series that are now sufficiently long (over twenty years for some instruments), these datasets could be valuable for downscaling applications. However, their use in climate projection remains limited, with few use cases or peer-reviewed articles available. Several challenges hinder the broader adoption of EO data in downscaling applications. Preprocessing EO data is often complex and requires specialized methods to ensure quality and compatibility. For example, the evolution of sensor technologies over time can introduce discontinuities in the data, complicating the creation of consistent long-term records. Fortunately, consistent EO-based data sets are provided by organisations such as, EUMETSAT and ESA in Europe, and NOAA and NASA in the USA. Nevertheless, challenges remain. For instance, statistical downscaling typically relies on observations and model outputs from the same time period, but these may not always be available due to varying satellite revisit times, which can range from a few days to over a week. Moreover, the variables derived from EO data often differ from those used in climate models or in-situ measurements. For example, EO data typically provide land surface temperature, whereas ground-based stations report — and users are generally more familiar with — air temperature measured at two metres above the ground. Taking this into account requires additional modelling, which complicates things and adds another source of uncertainty.

Despite these challenges, integrating EO data into downscaling offers significant opportunities for innovation, particularly in regions with sparse observational networks. Continued development of harmonised datasets and modelling techniques will be essential to leverage EO data fully in future climate services.

4. Guidelines for Using Climate Data in Risk Assessment

Based on the experience gained during the project, we have developed guidelines that may be useful for municipal and city representatives for selecting and using climate data effectively for climate indicators,

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considering uncertainty, resolution, and usability. It also shows some examples of how climate data has been visualized in the VALORADA dashboards.

4.1 Choosing climate data for the future

4.1.1 Use Multiple Models and Emission Scenarios

Future climate projections are inherently uncertain due to several key factors (see, e.g., Annex 1). A major source of uncertainty is the future level of greenhouse gas emissions and other anthropogenic forcings, which depend on societal choices regarding energy, land use, and mitigation policies (as depicted in Annex 1, Figure 1). To account for these uncertainties, multiple emission and socio-economic scenarios are used. Another source is the structural and parametric uncertainty in climate models themselves, as no single model can fully represent all physical, chemical, and biological processes in the Earth system. Natural climate variability adds further unpredictability, especially on shorter time scales and at regional scales. In addition, future land use changes, urbanisation, and ecosystem responses may evolve in ways that are not fully captured in climate projections, further increasing uncertainty in impact assessments. Therefore, one should not rely on a single climate model or emission scenario. Using a range of models (e.g. CMIP6 or EUROCORDEX ensemble) and multiple emission scenarios (e.g. SSP2-4.5, SSP5-8.5) provides a better representation of uncertainty and helps identify robust trends.

4.1.2 Model Skill in Simulating Recent and Present-day climate

Assessments how well climate models simulate recent and present-day climate help to identify models that perform well for your region and variables of interest. The model's ability to simulate the recent climate well enough is a necessary condition before one can trust it to forecast the future climate. If independent observations are available, quantitative evaluation is possible, if not, qualitative evaluation is possible, for example, by comparing visualizations of reanalyses with the current climate.

4.2 Understanding resolution and its limitations

4.2.1 Choose Resolution Based on the Use Case

The spatial and temporal resolution of the data should be matched to the application. Strategic planning may only require coarse resolution data (10–50 km), while local-scale adaptation measures may benefit from higher resolution (≤ 5 km) information.

4.2.3 When High Resolution Adds Value – and When It Doesn’t

Higher resolution does not guarantee higher accuracy or better results. Be cautious about over-interpreting fine-scale details, especially if uncertainties in the underlying model data are large. For instance, urban heat islands or complex terrain may benefit from high resolution, while regional mean temperature changes may not. For homogeneous flat regions increasing resolution may not significantly change the simulated climate, as large-scale patterns are already well captured by coarser models.

The challenge lies not only in the spatial resolution of climate variables, but also in the adequacy of the models used to translate these variables into meaningful impact indicators. For example, without reliable hydrological modelling – whether based on physical models or machine-learning models trained on historical events – it is difficult to assess the impact of extreme precipitation days on flood extent in a specific area. In such cases, the value of highly detailed climate data alone is limited. This is particularly true when such data may also carry higher levels of uncertainty.

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4.3 Visualising Climate Data

4.3.1 Show Model Spread and Scenario Differences

Avoid focusing only on ensemble means. The model spread, the range of values from the ensemble of the used different climate models, will help in assessing the uncertainty. In addition, use, for example, boxplots, fan plots, and probability ranges to communicate uncertainty and scenario differences. The figure below shows an example from the VALORADA climate dashboard, visualising climate data with the likely range from the model ensemble.

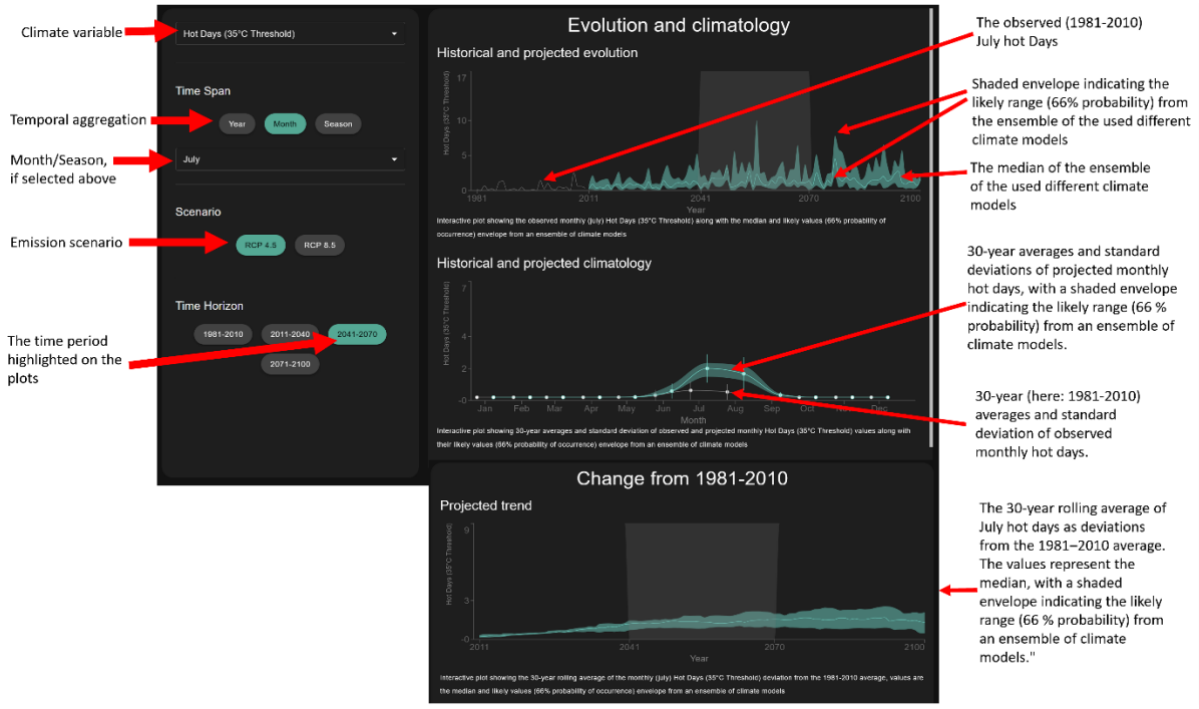


Figure 3. Screenshot of an example plot of the VALORADA climate dashboard presenting observed (1981-2010) and projected July hot days (daily maximum temperature ≥35 °C) from climate model ensembles. Climate data source: Climate indicators for Europe from 1940 to 2100 derived from reanalysis and climate projections (https://cds.climate.copernicus.eu/datasets/sis-ecde-climate-indicators).

4.3.2 Use Meaningful Colour Scales and Captions

Carefully selected colour scales and clear figure captions are essential for interpreting climate data visualisations. Avoid misleading visual emphasis. For example, note the difference between sequential and diverging colour scales. Avoid colour scales challenging to persons with colour blindness. There are guidelines available, see, for example, Crameri et al. (2020) and Stauffer et al. (2014). Luckily nowadays many visualization or GIS software offer reasonable colour scales as default.

4.4 Understanding and Communicating Uncertainty

4.4.1 Uncertainties Remain After Downscaling and Bias Correction

Downscaling relies on the outputs of larger-scale models, which are subject to uncertainty due to an incomplete understanding of climate processes. But downscaling cannot eliminate these inherent uncertainties of the original climate model data. This is related to our earlier note that higher resolution does not guarantee higher accuracy or better results. Be transparent about these limitations when using and communicating results.

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Bias correction helps improve the agreement between model simulations and observations. However, it must be applied carefully, as it can introduce its own uncertainties.

4.4.2 Uncertainty in the Climate Impact Chain

Each step from raw climate data to impact indicators (e.g. drought index, number of hot days) introduces additional uncertainty. Document the chain and highlight key sources of variability. For example, in VALORADA, the indicator for the irrigation water needs of crops assesses the water balance of a field by comparing water inputs with plant water use through evapotranspiration, based on climate variables (temperature and precipitation), types of crops, and soil characteristics. At each stage—from the accuracy of climate variables to the assumptions about crop growth and soil water retention—uncertainty is introduced, which can compound along the chain and affect the reliability of the final indicator.

4.4.3 The Problem of Unknown Future Land Use

Many climate projections assume that land use remains constant or is modelled with rather simple models (see, e.g., Wouters, H., et al. 2017). However, in regions undergoing rapid urbanisation or deforestation, this can lead to misleading conclusions. Cities, in particular, are constantly changing due to local planning and decision-making processes. It would be difficult for climate modellers to accurately take these changes into account because they do not have access to all the specific decisions being made at the local level, nor can they predict what kind of decisions will be made in the future. Consequently, the projections may not fully capture the impact of urban development on local climate conditions. Deforestation is also subject to future policy decisions which are not yet known.

5. Conclusions

In summary, our findings demonstrate that high-resolution climate model datasets—up to 1 km spatial resolution—can be effectively applied for climate risk assessments at the urban scale, tailored to specific sectors and regions.

Nevertheless, downscaling is a useful but limited tool: both dynamical and statistical methods can improve local climate risk assessments, but they do not remove uncertainties. The suitability of a downscaling approach depends on the use case, and the choice of method, resolution, and models should always be based on the accuracy requirements of the question and the availability of reference data. More reliable assessments are achieved by using multiple models and emission scenarios, and by evaluating model skill against past and present-day climate. Data must be used with understanding: cities and other stakeholders should be aware of the limitations of downscaled data and ensure that interpretation is carried out in collaboration with climate experts.

For cities, the added value of downscaling lies in its ability to better capture local conditions—such as topography, coastline effects, or urban heat islands—making climate indicators more relevant for urban impact assessments. This value increases when data are delivered in accessible formats and clear visualizations, such as maps and dashboards like the VALORADA dashboards. However, cities should be aware that downscaled data cannot exceed the quality of the original climate models, and that key factors such as future land use are rarely included unless explicitly modelled. The reliability of results also depends on the availability of local observations for calibration and validation, and there is no universally best downscaling method—choices should match information needs, resources, and context. Asking targeted questions to data providers about models, scenarios, methods, resolution, limitations, and uncertainty communication can help ensure responsible and effective use.

EO data offer valuable complementary information to in-situ observations and reanalyses, providing independent measurements with high spatial resolution and increasingly long time series. These strengths make them promising for downscaling applications, especially in regions with sparse observational networks. However, their use in climate projections remains limited due to challenges such as complex preprocessing (including sensor-related discontinuities and temporal gaps in satellite coverage) and mismatches between EO-derived variables and variables users need and are comfortable to work with. In conclusion, overcoming these limitations through

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harmonised datasets and improved modelling techniques will be key to unlocking the full potential of EO data in future climate services.

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7. Annex 1: Key Sources of Uncertainty in Climate Projections

Future climate projections are inherently uncertain due to several key factors. A major source of uncertainty is the future level of greenhouse gas emissions and other anthropogenic forcings, which depend on societal choices regarding energy, land use, and mitigation policies (see Figure 1).

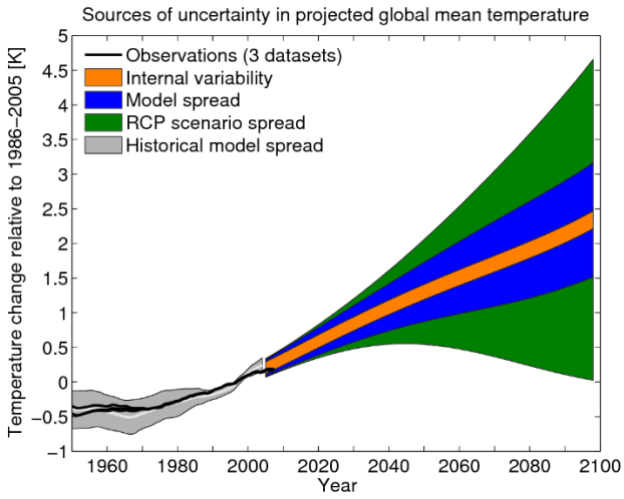


Figure 1. Sources of uncertainty in climate projections as a function of lead time based on an analysis of CMIP5 results. Projections of global mean decadal mean surface air temperature to 2100 together with a quantification of the uncertainty arising from internal variability (orange), model spread (blue) and RCP scenario spread (green). (Figure source IPCC, 2013) The sources of uncertainty in global decadal temperature projections, expressed as a 'plume' with the relative contribution to the total uncertainty coloured appropriately. The shaded regions represent 90% confidence intervals.

To account for these uncertainties, multiple emission and socio-economic scenarios are used. Another source of uncertainties are the structural and parametric uncertainties in climate models themselves, as no single model can fully represent all physical, chemical, and biological processes in the Earth system. Natural climate variability adds further unpredictability, especially on shorter time scales and at regional scales. In addition, future land use changes, urbanisation, and ecosystem responses may evolve in ways that are not fully captured in climate projections, further increasing uncertainty in impact assessments. Using a range of models (e.g. CMIP6 ensemble) and multiple emission scenarios (e.g. SSP2-4.5, SSP5-8.5) provides a better representation of uncertainty and helps identify robust trends.

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8. Annex 2: Dynamical downscaling

Dynamical downscaling employs Regional Climate Models (RCMs) to simulate climate behaviour over a smaller area with higher resolution. The process involves using boundary data from a GCM as input to the RCM, which then simulates climate and weather conditions over a more detailed, localized area. The results of this process are produced at a higher resolution, for example at 10-50 km horizontal resolution, e.g., over Europe (EURO-CORDEX; Jakob et al. 2020, Benestad et al. 2021). This method accounts for local geographical features such as mountains, lakes, and coastal areas, providing more accurate and locally relevant climate predictions. However, dynamic downscaling requires significant computational resources and is a time-consuming and complex process.

The added value of dynamic downscaling by regional climate models (RCMs) can be evaluated in two interrelated aspects: (1) an improved representation of the present-day climate and (2) a more precise projection of future climate changes. Although RCMs and general circulation models (GCMs) generally share similar computational frameworks, the enhancements primarily arise from the finer grid spacing used by RCMs. However, the added value is not always evident and can depend on the metric used and the type of comparison. This is particularly true for average features over large spatio-temporal scales (such as seasonal mean values averaged over extensive regions), which can often be adequately represented by coarse-resolution models.

Added value of the dynamic downscaling is typically more pronounced for mesoscale atmospheric phenomena (e.g., Feser et al., 2011), regional-scale climate variability and its future changes, especially in areas with complex surface features (such as topography, land use, and land-sea contrasts; e.g., Di Luca et al., 2013; Torma et al., 2015), and for the extremes in frequency distributions at high temporal resolution (e.g., daily extremes; Jacob et al., 2014). Generally, added value of dynamic downscaling is more likely to be observed for precipitation than for temperature (Di Luca et al., 2013, Ban et al., 2014).

Besides the advantages at high temporal and spatial resolutions, there are strong indications that RCMs can enhance their driving GCMs' performance even for aggregated large-scale mean values, which are generally resolved by the GCMs themselves (Kerkhoff et al., 2014; Torma et al., 2015). However, whether this results in a better depiction of both current and future climate is not always certain. Despite the clear advantages of RCMs for many aspects of present-day climate and projected climate change patterns, it is important to note that any RCM-based climate scenario is highly dependent on its driving GCM (Christensen and Kiellström, 2020). The quality and accuracy of a regional climate change scenario are thus determined by both the RCM and the driving GCM. Considering only one RCM-GCM combination represents just one of many possible outcomes. To comprehensively capture the range of potential outcomes and the associated uncertainties for specific RCMs and/or GCMs, it is essential to conduct ensemble simulations that combine different RCMs with different GCMs.

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9. Annex 3: Statistical downscaling

Statistical downscaling relies on analyzing and utilizing statistical relationships between historical climate and weather data and the data produced by larger-scale climate models. Statistical downscaling methods include a range of approaches that vary in complexity and application focus. One widely used class of methods is bias correction, which adjusts systematic biases in climate model outputs based on historical local observations (e.g., Gudmundsson et al., 2012; Veijalainen et al., 2012). It includes methods such as quantile mapping and variance scaling, which are often applied to align the distribution of daily temperature or precipitation data from models with observed records (Gudmundsson et al., 2012; Maraun, 2016). These approaches are computationally efficient and suitable for correcting both mean values and variability, but they rely on high-quality observational datasets.

Another approach involves the use of stochastic weather generators, which simulate realistic daily weather sequences based on the statistical properties of historical observations. These methods, such as LARS-WG, are particularly useful for generating long time series consistent with observed variability (Semenov & Stratonovitch, 2010). Weather generators are often employed when only coarse model output (e.g. monthly means) is available and finer temporal resolution is required.

For extreme events, extreme value theory provides tools to estimate changes in the frequency and intensity of rare climate phenomena. Generalized Extreme Value (GEV) fitting is commonly used to model the statistical behaviour of extremes, such as heavy rainfall or heatwaves, and to project changes in return levels under future scenarios (Coles, 2001).

Analogue and resampling methods identify historical periods with similar large-scale atmospheric conditions to current or projected model outputs. These analogue-based techniques estimate local conditions based on observed analogues, making them intuitive and transparent. However, they may struggle to provide reliable information in a future climate that diverges significantly from the historical record (Timbal & Jones, 2008).
Finally, regression-based techniques model the statistical relationship between large-scale climate predictors and local-scale responses. These can be linear models, such as Generalized Linear Models (GLMs), or more advanced non-linear methods based on machine learning. Recent studies have demonstrated the potential of techniques such as decision trees, random forests, and deep learning to capture complex, non-linear dependencies in the climate system (Rampal et al., 2024; Hernanz et al., 2024). Techniques such as deep learning, decision trees, and random forests have shown potential to improve prediction accuracy. However, their application comes with challenges related to data requirements, model generalisation, and interpretability, highlighting the need for careful validation and transparency in method development.
The process of statistical downscaling involves several key steps. First, historical climate data, such as temperature and precipitation, is collected from observational networks like weather stations. In parallel, data from larger-scale climate models (GCMs) is gathered as input. Statistical relationships between the historical local observations and the data from larger-scale climate models are then analyzed. These established statistical relationships are used to convert predictions from larger-scale climate models into localized climate data.
The advantage of statistical downscaling is that it is less computationally demanding than dynamic downscaling and can be a fast and straightforward process. However, as statistical downscaling relies on establishing empirical relationships between large-scale climate model outputs and local climate conditions, this process necessitates comprehensive local observational data to accurately calibrate and validate these relationships. Therefore, in the absence of sufficient local observational data, it is impossible to perform statistical downscaling effectively. The lack of observational data means that the necessary links between broad-scale climate predictors and regional or local climate responses cannot be reliably quantified. Consequently, the absence of this data precludes the ability to generate precise high-resolution climate projections using statistical downscaling methods.

Moreover, statistical downscaling methods rely on the assumption that historical statistical relationships will remain valid under future climate conditions. This assumption can be problematic for several reasons. Climate change may result in future climate conditions that differ significantly from current or historical conditions. Extreme weather events, in terms of their frequency and intensity, could change in ways that historical statistical relationships cannot accurately predict. Moreover, systemic changes, such as alterations in atmospheric circulation patterns or ocean currents, might affect local climate conditions.
Additionally, historical statistical relationships may not fully account for complex feedback mechanisms and indirect effects that could evolve in the future. For example, changes in land surface, like deforestation or

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urbanization, could alter local climate conditions in ways that historical data does not capture. Variations in greenhouse gas concentrations and their effects might also impact the climate system in complex ways.
The assumption of linear changes in historical statistical relationships can be another limitation, as climate change impacts can be non-linear. Small changes may lead to significant and unpredictable effects at the local level.
Examples of the applicability and challenges of statistical methods include empirical and regression models, which can be useful for short-term forecasts but may be uncertain for long-term predictions. Analogue methods, which rely on similar historical conditions, might not be applicable if future conditions are unique. Newer methods like machine learning and AI can enhance prediction accuracy but still depend on historical data and face similar challenges.
In summary, statistical downscaling is a useful and efficient method for localizing climate model data, but its application involves significant challenges, especially concerning the validity of historical relationships in the future. Therefore, it is crucial to combine statistical and dynamic downscaling methods, use diverse scenarios, and account for potential uncertainties in climate predictions.

Temporal Downscaling: Improving the Temporal Resolution of Climate Data
In addition to spatial detail, many climate risk assessments require high temporal resolution data. Climate model outputs are often provided as long-term monthly or seasonal means, which are insufficient for applications involving daily or sub-daily variability, such as heat stress, flash flooding, or fire danger.
One solution is to directly use high-frequency output from global or regional models where available. Many CMIP6 and CORDEX simulations provide daily or even sub-daily data (Jacob et al., 2014; Coppola et al., 2021), although data volume and availability can be limiting factors in practice.
When high-frequency model output is unavailable, statistical temporal disaggregation methods are used to estimate finer-resolution data from coarser inputs. For instance, stochastic weather generators can simulate daily temperature and precipitation sequences that replicate observed variability (Semenov & Stratonovitch, 2010). Other approaches include stochastic disaggregation, which breaks down monthly or seasonal values into daily estimates using observed temporal patterns, and resampling techniques, which select historical daily sequences that match projected monthly or seasonal means. In addition, scaling methods apply empirical relationships to interpolate between time scales.
These methods have been applied in European studies to generate daily weather input for hydrological models, crop growth simulations, and drought indices (Driouech et al., 2009).
When daily output from climate models is available but exhibits biases, bias correction techniques such as quantile mapping, variance scaling, or GEV fitting can be applied to ensure realistic representation of daily variability and extremes (Gudmundsson et al., 2012).

It is important to note that temporal downscaling does not introduce new physical information; it infers finer-scale variability based on statistical assumptions. The quality of the results is highly dependent on the availability of high-resolution observational data for calibration and validation. Moreover, temporal disaggregation methods often assume stationarity in statistical relationships, which may not hold under future climate change, particularly for processes involving extremes or non-linear feedbacks.
Temporal downscaling is most valuable in applications that depend on daily or sub-daily data. For instance, fire danger indices such as the Fire Weather Index depend on daily temperature, humidity, wind, and precipitation, and drought monitoring frequently uses daily SPEI or SPI indices (Spinoni et al., 2015).

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10. Annex 4: Overview of available free statistical downscaling tools

There are many open-source software packages for statistical downscaling of climate data available. However, many packages stop development once the initial project ends. Here, we have selected packages that are still being updated and were developed by well-known research institutes or NHMSs.

For R, the most established packages are perhaps:

downscaleR from the climate4R library (https://github.com/SantanderMetGroup/downscaleR, Iturbide et al. 2019),

ESD (https://github.com/metno/esd/ ,Benestad et al. 2015),

CSDownscale, which is based on the CSTools library (https://earth.bsc.es/gitlab/es/csdownscale ,

Pérez-Zanón et al. 2022).

These packages all implement standard downscaling methods, but they require at least moderate programming skills to use.

For Python, there are:

xclim (https://github.com/Ouranosinc/xclim,

Bourgault et al. 2023)

pyClim-SDM (https://gitlab.aemet.es/aemc/scenarios/pyClim-SDM, Hernanz et al. 2023). The pyClim-SDM offers a graphical user interface but still requires moderate programming skills to build the system.

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