



D3.2 – Extreme value distributions for Europe – present climate

Project name

Asset Level Modelling of RISKS In the Face of Climate Induced Extreme Events and ADAPTtation (RISKADAPT)

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List of Abbreviations and Acronyms

Abbreviation	Meaning
CC	Climate Change
CDS	Copernicus Climate Data Store
CMIP6	Coupled Model Intercomparison Project Phase 6
CORDEX	Coordinated Regional Downscaling Experiment
E-OBS	CDS daily gridded meteorological data
ECMWF	European Centre for Medium Range Weather Forecasts
EO	Earth Observation
ERA5	fifth generation ECMWF reanalysis
GEOSS	Global Earth Observation System of Systems
GEV	Generalised Extreme Value
GPEX	Global Precipitation Extremes data set
HBV	conceptual hydrological model from GloH2O project
IDF	Intensity Duration Frequency
LCC	Life Cycle Cost
LES	Large Eddy Simulation
MCMC	Markov Chain Monte Carlo
MIS	Model Information System
MIS	Model Information System
MIS	Model Information System
PALM	Modeling system for atmospheric and oceanic boundary layer flows
WP	Work Package

Executive Summary

RISKADAPT will provide, in close cooperation with the end-users/other stakeholders, a novel, integrated, modular, interoperable, public and free, customisable user-friendly platform (PRISKADAPT), to support systemic, risk-informed decisions regarding adaptation to Climate Change (CC) induced compound events at the asset level, focusing on the structural system. PRISKADAPT will explicitly model dependencies between infrastructures, which, inter alia, will provide a better understanding of the nexus between climate hazards and social vulnerabilities and resilience. Moreover, this project will identify gaps in data and propose ways to overcome them and advance the state of the art of asset level modelling through advanced climate science to predict CC forcing on the structure of interest, structural analyses, customised to the specific structure of interest, that consider all major CC induced load effects in tandem with material deterioration, novel probabilistic environmental Life Cycle Assessment (LCA) and Life Cycle Cost (LCC) of structural adaptation measures and a new model to assess climate risk that will combine technical risk assessment with assessment of social risks. PRISKADAPT will provide values to a set of indicators for each asset of interest, quantifying primary parameters and impacts, in the form of a Model Information System (MIS) that will provide all required information for adaptation decisions. PRISKADAPT will be implemented in the case studies in the pilots that involve specific assets, however, it will permit customisation with local values of parameters and data, so it can be applicable throughout Europe for CC adaptation decisions involving assets of similar function, exposed to multiple climate hazards.

The current report is one of the three deliverables of WP3 “Climate Data, CC Forcing, Multi-Hazard Modelling” and corresponds to T3.1: “Climate data for hydrological analyses, wind and rain forcing and material degradation. Extreme Value Analyses” of the RISKADAPT project. To meet the aim of this Task, in this report the terminology, methods and tools that can be used to perform statistical extreme value analysis on climate data are presented. Climate (input) data can mainly come from reanalysis data (like ERA5) or from in-situ time series measurements. In addition, and as the focus of this report is on the analysis of present climate, i.e., approximate for years 1970-2020, pointers to Copernicus CDS data sets and tools are provided that can be used to evaluate risks caused by extreme events for infrastructure, especially those that are related to project’s pilots.

1. Introduction

In the RISKADAPT project extreme value distributions are used to study climate data for hydrological analyses, wind and rain forcing, and material degradation. Extreme value analyses will be performed to the relevant climatic variables and parameters that have been identified in WP2. For the present climate, focus is especially on the state-of-the-art C3S CDS reanalysis data and E-OBS in-situ data, both available from the C3S CDS. The next deliverable, D3.3, will focus more on the future climate and the effect of climate change on extreme values. For the CC data, the focus will be on the regional CORDEX data as well as on the most recent global climate projection data CMIP6. In WP3 Task 3.1, Bayesian hierarchical approach to extreme value analysis will be applied, allowing us to account for spatial and temporal dependencies on the variables and to study the temporal evolution of the distributional parameters.

1.1 Purpose of the deliverable

The purpose of this Deliverable is to describe the available sources of climate data that can be used as input for extreme value analysis. In doing this, the statistical analysis that can be performed to monthly or yearly maxima of quantities of interest is described; the difficulties in obtaining the data as well the adequacy of available reanalysis data sets in terms of spatial and temporal resolution are explained; and the need for further downscaling of results is also discussed.

The objectives related to this deliverable have been achieved, however there was a two-month delay in submitting the deliverable. This was mostly due to not being able to formulate the needs of the partners in terms of extreme value analyses. This is still a work in progress in the time of writing this proposal.

1.2 Structure of the deliverable

The Deliverable has been structured as follows:

- Chapter 1. Describes the aim of the RISKADAPT project as well as the purpose, the intended audience and the structure of this document.
- Chapter 2. Describes extreme value analysis and data sources relevant to RISKADAPT project. There are three Python notebooks included in the Annexes that provide examples of analyses that are possible with the current data sources.
- Chapter 3. Summarises the main outcomes of this Deliverable and outlines the future work.

1.3 Intended audience

As the dissemination level of this Deliverable is public, it will be openly available to all RISKADAPT partners, as well as other stakeholders, such as public authorities, infrastructure owners and operators, researchers and technology providers, interested in a report that presents the basic terminology related to extreme value analysis.

2. Extreme values and climate

2.1 Introduction

Extreme weather can mean weather phenomena that are rare in climatological sense. For example, if the average return period of occurrence is more than 30 years. Or it can mean weather events that causes extreme damage, like heavy rain, wildfires, or heat waves, even if they are not rare in statistical sense. In this report, we concentrate on climatological features of weather-related variables, mostly for temperature, wind speed and precipitation, as they are relevant in RISKADAPT project's pilots and other tasks. One special quantity of interest is icing, that is target of Task 4.4 in WP4 as well as of Pilot 2. As there are not enough direct observational icing data, we need to use icing models. These models take as input several weather variables, such as temperature and the amount of liquid water in the clouds. The different approaches to study extreme icing will be discussed in more detail below.

The previous deliverable D3.1 for RISKADAPT WP3 described different sources of EO data that can be used in the analyses of the project. The main data sources were the Copernicus Climate Data Store (CDS): ERA5 reanalysis, E-OBS observation analysis, and CMIP6 regional climate model runs. Other important sources mentioned were the GEOSS Global Earth Observation System of Systems as well as data from national and regional weather institutes that provide open access to their data, both to observations and model output. For extreme value analysis, we will be utilizing the same sources and provide examples on how specific questions can be answered based on the available data. We provide Python code for downloading the data and calculating return periods for quantities of interest based on statistical extreme value theory.

2.2 Statistical extreme value analysis

Statistical extreme value theory is based on the fact that the maximum value in a set of random numbers follows, under quite general assumptions, a distribution called generalised extreme value distribution, GEV. The same applies to the minimum with a change of variables. When we know the statistical distribution of the phenomena of interest, we can draw inference on the occurrence probabilities and risks related to the event. In extreme value terminology, the things of interest are called return periods and return levels. These are defined shortly below.

In specific the classical extreme value theory is described as it is typically used in climate science in addition to the use of Bayesian terminology and methods, which allows to discuss the relevance of prior information about model parameters and their correlation. Standard reference to statistical extreme value theory is by Coles (2001). Some other relevant literature on extreme value analysis of climate include works by AghaKouchak (2011) and Hamdi (2021).

The cumulative distribution function of GEV can be written with the help of three parameters, location μ , scale σ , and shape ξ as

$$G(y; \mu, \sigma, \xi) = \exp\left(-\left[1 + \xi \left(\frac{y - \mu}{\sigma}\right)_+^{-\frac{1}{\xi}}\right]\right), \quad (1)$$

where y is the quantity of interest, such as yearly maximum temperature, μ , σ , and ξ are the model parameters and subindex $+$ means taking maximum with zero. This equation directly leads to quantiles of the distribution as

$$y_p = \begin{cases} \mu - \frac{\sigma}{\xi} [1 - \{-\log(1 - p)\}^{-\xi}], & \text{for } \xi \neq 0, \\ \mu - \sigma \log\{1 - \log(1 - p)\}, & \text{for } \xi = 0. \end{cases} \quad (2)$$

This equation is used to calculate the return level y_p associated with a certain exceedance probability p or equivalently, the return period $T = 1/p$.

There are several approaches to estimate GEV distribution parameters given time series of occurrences of the quantity of interest. In the most basic cases we are assuming a stationary situation, where a set of fixed values of the parameters (μ , σ , and ξ) would explain the behaviour of the phenomena in a given geographical location. If this is the case, the equation (2) would directly give return levels corresponding to given return periods. For the estimation of parameters, we assume having a number of independent realizations of the extreme values which can be used to find a specific version of GEV that can reproduce the observed values. When an estimate is based on a finite number of observations, the estimate will have uncertainty, which is important to quantify for proper use in further analyses. Bayesian analysis is a suitable tool for this. We can base the analysis of uncertainties to MCMC simulation, which is a computational technique that provides samples from Bayesian uncertainty distributions of model parameters and model derived quantities.

As an example, let's consider IDF curves for precipitation. They are standard tools for managing rainfall data in environmental engineering. The curves show rainfall intensities and durations for given return period frequencies. IDF curves are location-specific, meaning that they need to be developed for each specific geographic area based on local rainfall data. They are a valuable tool for assessing and managing the risks associated with precipitation-related events. An example of calculating IDF curves from the precipitation extremes is provided below. Figure 1 shows IDF curves for Haliacmon river drainage basing calculated using GPEX data. These curves can be used in hydrological analysis related to Pilot 1.

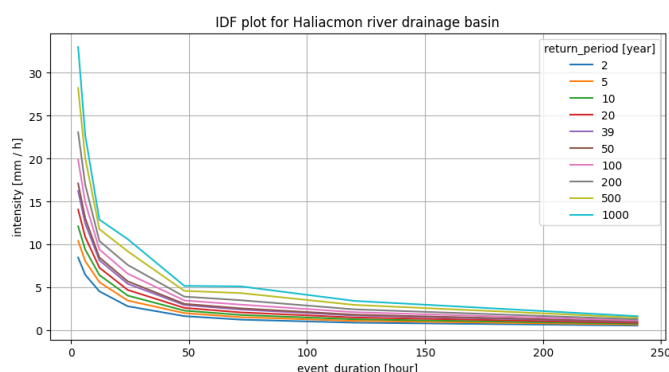


Figure 1. IDF curves that provide information on return periods of precipitation events of different intensity and duration. The data is averaged over the Haliacmon river drainage basin.

2.3 Climate variables

To analyse risks on the infrastructure, the effects of weather need to be considered. For example, when building near shore, one must account for the maximum water levels and since this will depend on random external events as well as on changes in the future climate, it is needed to think in terms of probabilities and risks.

Extreme weather events, such as extreme temperature or precipitation, are becoming the dominant factor in the causes of disasters that affect the safety of critical assets, like buildings and bridges, with long life span. Climate change will alter the frequency and effect of these phenomena, and it is important to be able to quantify the expected changes in risks and integrate climate change aspects into the adaptation planning process of existing structures and in the planning process of new structures.

In the RISKADAPT project, special attention is given to those climatic variables that affect critical infrastructure. The project pilots target bridges and buildings that are affected by heavy winds and rainfall. In addition, Pilot 2 studies the effect of icing on the energy transmission lines in northern

countries. This means that variables of interest will be related to temperature, wind, precipitation, and river discharges, as well as those needed in modelling of ice formation, such as cloud water content.

2.4 Available data

The data sources that are utilized were described in deliverable D3.1. These sources include data available from Copernicus services, data provided from previous research projects, and various sources of in-situ time series. Historical reanalyses are useful as they provide complete, both time and space, reconstruction of the climate¹. The drawback is that the resolution can be quite sparse. For example, ERA5 is delivered in spatial resolution of 0.25° (about 30 km), and ERA5 Land and E-OBS in 0.1°. In-situ or remote sensing observation archives give more accurate representation at a specific location, but they are spatially and temporally sparse. As an example of the effect of resolution, shows the location of Cattinara Hospital in Trieste, Italy (Pilot 3), with data pixels from four different reanalysis data sets. The colouring shows whether the pixel is considered land or sea by the data.

There are some specific high-resolution data sets available from separate previous studies. For example, Pirinen (2022) provide 1 km x 1 km resolution daily gridded evapotranspiration dataset covering Finland over the 40-year period 1981–2020 that is based on in-situ rain gauge observations which are spatially interpolated using Kriging method.

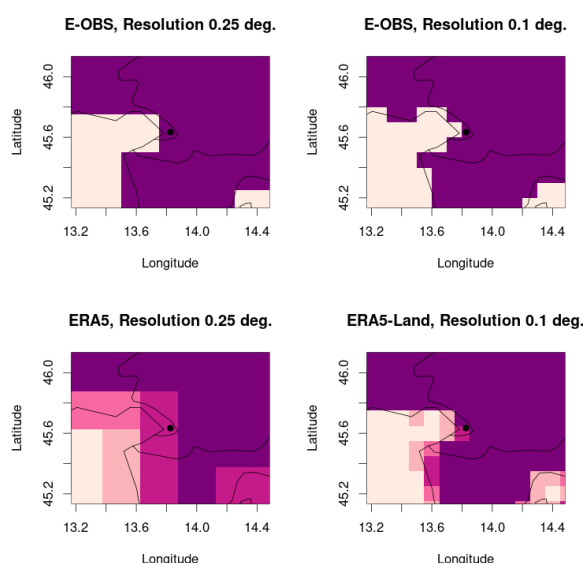


Figure 2. Location of Cattinara Hospital in Trieste, Italy within four different data sets. The darkest colour means land pixel, lightest is sea, while some pixels are considered as being in-between by the data set's land-sea-mask.

For climatic extreme values there are some previous projects that provide data openly for use. One example is GPEX data set (Gründemann, et al. 2023), which contains global extreme precipitation return levels. The data is available for download, and it has precipitation levels for several precipitation durations and return periods ranging from 2 years to 1000 years. From this data set, one can extract the area of interest, such as the Heliacmon river drainage basin (

¹ <https://www.ecmwf.int/en/about/media-centre/focus/2023/fact-sheet-reanalysis>

Figure 3) that is used in Pilot 1 of RISKADAPT for studying return times of extreme precipitations events for hydrological analysis. In Figure 1 above, intensity-duration-frequency (IDF) curves calculated using the precipitation extremes in the GPEX data set and averaging the results over pixels that cover the drainage area were presented.

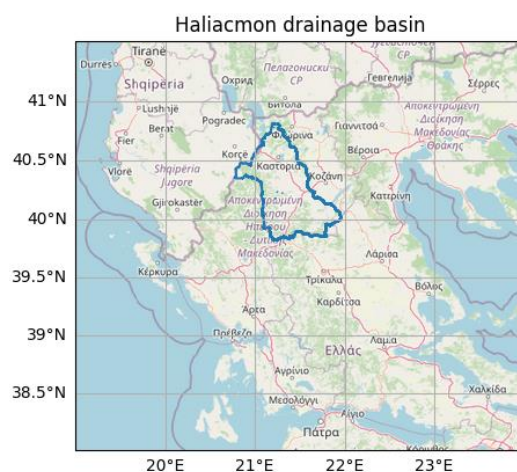


Figure 3. Haliacmon river drainage basin that is used in RISKADAPT Pilot 1.

The GMEX data is produced using climate data from the GloH2O project (<https://www.gloh2o.org>), which provides high-resolution, bias-corrected weather data for the past, present, and future. They have several interesting data sets, such as regionalized parameter maps for the conceptual hydrological model HBV covering the entire land surface (<https://www.gloh2o.org/hbv/>). These will be useful for the hydrological analysis tasks in the RISKADAPT project.

2.4.1 Downscaling

Most climate reanalysis data are provided in spatial resolution of 10 to 50 km, and in temporal resolution typically in hourly intervals. There are very few km-scale reanalysis and the existing ones do not usually allow for extreme value analysis of longer return periods. However, in many studies there is a need for downscaling the results to finer temporal and spatial scale. In RISKADAPT the need for going from kilometer scale to even meter scale comes from the study of climate effects on individual constructions, such as buildings, bridges, or power transmission towers. For this reason, special methods are needed. But when the simulation results have been obtained, the statistical analysis for return periods is essentially the same.

If meter-scale analysis of wind fields is needed, one approach is based on performing small scale simulation runs with meteorological large-eddy simulation (LES) models, such as PALM (Maronga, 2015). These can be based on larger scale mean wind fields which are rescaled when studying the effect of extreme wind events on local scale. For additional information see the work by Hellsten (2021) and the PANOPTIS EU project².

2.4.2 Icing

² <http://www.panoptis.eu/>

RISKADAPT Pilot 2 and Task 4.4 consider the effect of atmospheric icing and especially ice formation on electric power lines. For this, a specific icing model is needed that can calculate the accumulation of ice on a surface based on variables that are available from numerical weather prediction models, climate model runs or from historical reanalyses. Herein the icing model defined in ISO 12494 (Makkonen, 2000) is used that is modified for climate model output. The model produces time series of accretion of rime ice on a cylinder based on cloud liquid water content, temperature, pressure, and wind speed. For proper analysis, one needs to decide what are the icing events, for example in units of g/h, that are of interest. Is the interest in the amount of icing, on the length of icing periods, and so on. Is the information on the maximum yearly amount of passive ice formation and its possible trend due climate change enough or do we need analysis of finer details. These details need to be decided before doing further analysis. In addition, the combined effect of icing and wind will be studied.

2.4.3 Obtaining and storing the data

Another challenge in extreme value analysis of climatic variables is that although many services can provide readily computed monthly means, they are not providing monthly maxima. For this reason, one might need to download or somehow access the whole data in the original temporal resolution and then extract the statistics needed. For hourly resolution and several decades, this will result to very large data files. For analysis on high resolution data on the CDS archive, part of the data collection can be done using the CDS Toolbox³, which saves from downloading large amounts of data. CDS has some useful pre-made applications that can be useful as well.⁴ They include:

- Global temperature trend monitor.
- Daily statistics calculated from ERA5 data.
- Extreme precipitation statistics for Europe.
- European hydrology seasonal forecast explorer.
- European hydrology and climate data explorer.

However, CDS and the provided CDS Toolbox applications can typically provide only limited amount of data at a time. In many cases, the user must download large data sets, extract extreme events of interest, and perform statistical analysis, which can be quite time consuming. For this purpose, it will be advisable to provide pre-calculated extremes, like monthly maximums of temperature, rain, and wind speed, and store them in RISKADAPT data management system, so that these can be easily accessed by project partners and by the PRISKADAPT platform that will be made later in the project. The use of user-friendly data formats and metadata is important for the usability.

2.5 Extreme value analysis examples

In the following some examples on extreme value analysis related to RISKADAPT Tasks are provided. Moreover, the Annex lists Python notebooks that describe the use of reanalysis data and the calculation of extreme value statistics. The examples concentrate on variables and locations that are relevant to the Pilots of the project. The code is available at <https://github.com/fmidev/RISKADAPT/>. The examples are listed in Table 1. In addition, a set of Python functions that can be used to fit a generalized extreme value distribution to a time series data and calculate return levels for given return periods is provided. The code uses Stan probabilistic language (<https://mc-stan.org>) to define the statistical model and calculate posterior probabilities for GEV parameters as well as for quantiles of the fitted distribution, which in turn can be used to calculate return levels and their uncertainties. The estimation is based on Markov chain Monte Carlo (MCMC) sampling. The statistical analysis is similar

³ <https://cds.climate.copernicus.eu/cdsapp#!/toolbox>

⁴ <https://cds.climate.copernicus.eu/cdsapp#!/search?type=application>

to Rätty et al. (2023), which studied maximum water levels for high-risk infrastructure of nuclear power plants located by the shore.

Table 1: Extreme values analysis examples

Example	Variables	Data set used	Years	reference
Extreme value analysis on ERA5 data	t2m, d2m, ws10, tp24	ERA5	1980-2019	GitHub link
ERA5 Land examples	temperature and wind speed	ERA5 Land	1980-2019	GitHub link
GPEX data	precipitation	GPEX	1979-2017	GitHub link

2.5.1 ERA5 extreme values

ERA5 reanalysis data from the Copernicus CDS service is the most comprehensive global reanalysis data. It has a large set of climate variables with 0.25 degree spatial and hourly temporal resolution. The data start from year 1940 and are continuously updated for present day values. Herein ERA5 is used as an example on obtaining extreme value analysis on the past and present climate. For extreme values, one is typically interested in maximum or minimum values over a long period, like month or year. As the CDS service does not provide these maxima directly, hourly data should be downloaded and aggregated values should be calculated locally. Fortunately, the CDS download tools allow for downloading limited geographical areas to make the download size smaller. However, it is advisable to use already downloaded data when possible. Many institutes store ERA5 and similar reanalysis data sets in their local storage systems. It is also possible to use cloud storages, such as Google Cloud or Amazon AWS for the analysis tasks.

In the examples provided, monthly maxima of 2-meter temperature, dew point temperature, wind speed in 10 m, and total precipitation in 24 hours are calculated for ERA5 pixels over the European domain. This allows us to perform monthly, seasonal, or yearly analysis in selected pixels or over aggregated areas. Generalized extreme value distribution can be fitted for the maxima to obtain the GEV parameters, which can be used to obtain return level estimates for given return periods. The analysis is done using Bayesian framework and by MCMC sampling, which provides predictive uncertainty distributions for the quantities of interest. Similar analysis was performed to maximum yearly water levels by Rätty (2023) and this reference can be used as introduction to the statistical analysis and software needed. Figure 4 shows August temperature maxima with an average return period of 20 years. The values are shown for four geographical locations. The density histograms show the uncertainty related to this estimate obtained from the MCMC simulation. This is important for risk management. For example, if one needs 95% certainty on the 20-year maximum August temperature at Trieste, one should be prepared for about 37 degrees Celsius. Using Bayesian analysis the risk analysis accounts for uncertainty in the estimated extreme value distributions based on limited observational evidence and thus making it more realistic.

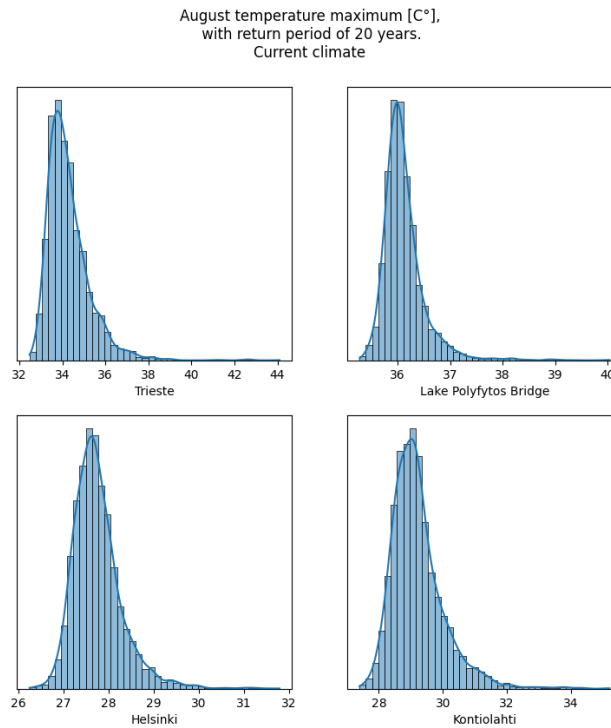


Figure 4. Temperature maxima from ERA5

2.5.2 Accounting for spatial and temporal correlation

In the provided ERA5 examples the analysis was performed for each spatial location separately. In addition, it was assumed that the climate does not change significantly during the period of the data used. In statistical terms, we assume stationarity in the distributional properties of the system. However, this is not always the case. The climate system is changing and analysis on historical observations does not necessarily provide accurate information for future extremes. On the other hand, data from one location has information on the behaviour at neighbouring locations. This can be used in advantage by pooling information from neighbouring sites and thus reducing uncertainties. An additional benefit is in the case of in-situ observations, where pooling can provide information for locations that are close to the observation locations. The aforementioned process was used by Rätty et al. (2023), where pooled information on water level gauge stations along Finnish coastlines was used. Figure 5 shows the estimated return level curves for yearly to thousand-year return periods. Without pooling the information, the uncertainty for rare events would have been much larger. The analysis in the paper was motivated by the needs of nuclear power plant safety.

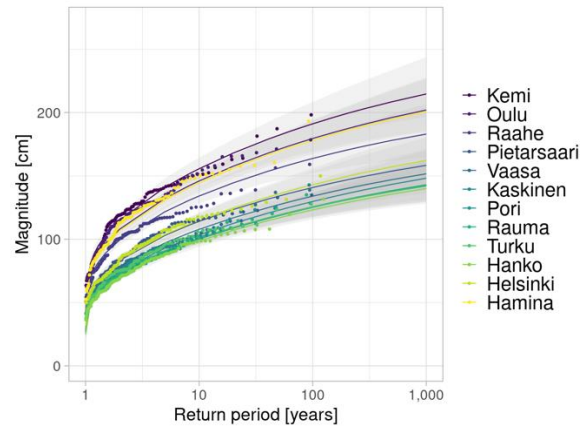


Figure 5. Analysis of extreme water level from Rätty et al. (2023). Hierarchical statistical model is fitted to parameters of GEV distribution. The dots show observed maximum yearly water levels. Solid lines are modelled values from GEV model for each 12 stations.

3. Conclusions

This deliverable report provided an overview of extreme value analysis on climate data. We provide several examples on extreme value analysis using openly available climate data. There is plenty of available data sets that are suitable for analysing extremes in the present climate. However, the spatial resolution is not necessarily sufficient for building level analyses performed in RISKADAP project. For that, advanced downscaling method might be needed.

References

- AghaKouchak, A., Easterling, D., Hsu, K., Schubert, S., & Sorooshian, S. (Eds.). (2012). *Extremes in a changing climate: Detection, analysis and uncertainty*. Springer Netherlands.
- Beck, H. E., Pan, M., Roy, T., Weedon, G. P., Pappenberger, F., van Dijk, A. I. J. M., Huffman, G. J., Adler, R. F., and Wood, E. F.: Daily evaluation of 26 precipitation datasets using Stage-IV gauge-radar data for the CONUS, *Hydrol. Earth Syst. Sci.*, 23, 207–224, <https://doi.org/10.5194/hess-23-207-2019>, 2019.
- Coles, S. (2001). *An Introduction to Statistical Modeling of Extreme Values*. Springer Verlag.
- Gründemann, G. J., E. Zorzetto, H. E. Beck, M. Schleiss, N. van de Giesen, M. Marani, and R. J. van der Ent. (2023). Extreme precipitation return levels for multiple durations on a global scale. *Journal of Hydrology*, 621:129558. <https://doi.org/10.1016/j.jhydrol.2023.129558>
- Hamdi, Y., Haigh, I. D., Parey, S., and Wahl, T.: Preface: Advances in extreme value analysis and application to natural hazards, *Nat. Hazards Earth Syst. Sci.*, 21, 1461–1465, <https://doi.org/10.5194/nhess-21-1461-2021>, 2021.
- Hellsten, A., Ketelsen, K., Sühling, M., Auvinen, M., Maronga, B., Knigge, C., Barmpas, F., Tsegas, G., Moussiopoulos, N., and Raasch, S.: A nested multi-scale system implemented in the large-eddy simulation model PALM model system 6.0, *Geosci. Model Dev.*, 14, 3185–3214, <https://doi.org/10.5194/gmd-14-3185-2021>, 2021.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R.J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., Thépaut, J-N. (2017): Complete ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate. Copernicus Climate Change Service (C3S) Data Store (CDS).
- Makkonen, L. (2000). Models for the growth of rime, glaze, icicles and wet snow on structures. *Philosophical Transactions of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, 358(1776):2913–2939, nov 2000. <https://doi.org/10.1098/rsta.2000.0690>.
- Maronga, B., Gryscha, M., Heinze, R., Hoffmann, F., Kanani-Sühling, F., Keck, M., Ketelsen, K., Letzel, M. O., Sühling, M., and Raasch, S. (2015): The Parallelized Large-Eddy Simulation Model (PALM) version 4.0 for atmospheric and oceanic flows: model formulation, recent developments, and future perspectives, *Geosci. Model Dev.*, 8, 1539-1637, DOI:10.5194/gmd-8-2515-2015
- Pirinen, P., Lehtonen, I., Heikkinen, R. K., Aapala, K., Aalto, J., (2022). Daily gridded evapotranspiration data for Finland for 1981–2020, *Clim. Bull. Res. Lett.* 4. <https://doi.org/10.35614/ISSN-2341-6408-IK-2022-11-RL>
- Räty, O., M. Laine, U. Leijala, J. Särkkä, and M. M. Johansson (2023). Bayesian hierarchical modelling of sea-level extremes in the Finnish coastal region. *Natural Hazards and Earth System Sciences*, 23(7):2403–2418, 2023. <https://doi.org/10.5194/nhess-23-2403-2023>.

Annexes

The following pages contain three examples on obtaining and processing reanalysis data and preparing them for extreme value analysis. It also includes Bayesian extreme value analysis for some variables. The examples are provided as Python language notebooks that contain the computer code used to perform the analysis. The source code is available from GitHub repository at <https://github.com/fmidev/RISKADAPT/>. The examples were listed in Table 1 and described shortly below. The repository contains extreme value analysis code that can be used to calculate further return periods of the quantities of interest.

ERA5 Land examples

These examples demonstrate the use of ERA5 Land data from the Copernicus service. It uses two locations related to RISKADAPT Pilots: Lake Polyfytos Bridge in Greece and Cattinara Hospital in Italy. The demonstration studies one month (August) from year 1980 to 2019 and calculates monthly maxima from the provided hourly data. It shows how total precipitation coming from hourly data can be accumulated into 24-hour total precipitation for each hour that is more usable for hydrological studies. For wind speed, the u and v components of wind are interpolated to a given location and transformed to wind speed.

GPEX data

This example uses Global Precipitation Extremes dataset GPEX. The data are described in detail in: Extreme Precipitation Return Levels for Multiple Durations on a Global Scale (Gründemann et al., 2021). Herein, data over Haliacmon river drainage basin were used and precipitation return levels for several event durations and return periods were extracted based on GEV analysis. In addition, Intensity-Duration-Frequency plots were formed over the study area.

Annex 1. Extreme value analysis on ERA5 data

In the following we demonstrate calculations of extreme value analysis for ERA5 variables. Similar analysis would be possible to other similar gridded reanalysis data sets. As ERA5 is a quite low resolution (0.25°) data set, extremes are bound to be smoothed. For more refined analysis, a higher resolution data could be used. For example, ERA5 Land has 0.1° spatial resolution.

```
import os
import warnings
import calendar
import numpy as np
import xarray as xr

import matplotlib.pyplot as plt
import seaborn as sns

warnings.simplefilter(action='ignore', category=FutureWarning)

DATA = os.path.expanduser('~'/DATA/RISKADAPT/')
```

Here we assume that we have precalculated monthly maxima of the ERA5 variables of interest.

```
era5 = xr.open_dataset(DATA+'ERA5_Europe_monthly_max.nc')
era5

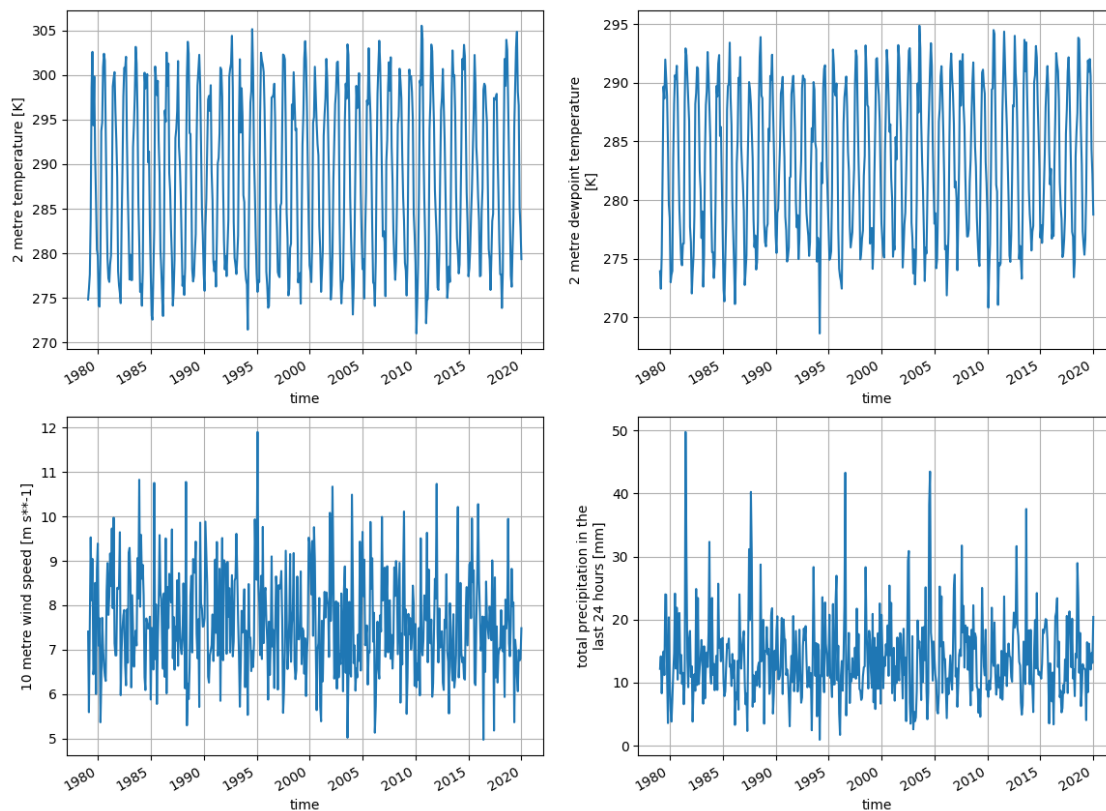
<xarray.Dataset>
Dimensions:      (time: 492, latitude: 187, longitude: 261)
Coordinates:
  * latitude      (latitude) float64 72.0 71.75 71.5 71.25 ... 26.0 25.75 25.5
  * longitude     (longitude) float64 -25.0 -24.75 -24.5 -24.25 ... 39.5 39.75 40.0
  * time          (time) datetime64[ns] 1979-01-31 1979-02-28 ... 2019-12-31
Data variables:
  t2m            (time, latitude, longitude) float32 ...
  d2m            (time, latitude, longitude) float32 ...
  ws10           (time, latitude, longitude) float32 ...
  tp24           (time, latitude, longitude) float32 ...
```

Plot the data at the selected lon lat points.

```
lon, lat = 25.0, 60.5

fig, axs = plt.subplots(2, 2, figsize=(14, 10))
era5['t2m'].interp(latitude=lat, longitude=lon).plot(ax=axs[0,0])
era5['d2m'].interp(latitude=lat, longitude=lon).plot(ax=axs[0,1])
era5['ws10'].interp(latitude=lat, longitude=lon).plot(ax=axs[1,0])
era5['tp24'].interp(latitude=lat, longitude=lon).plot(ax=axs[1,1])
for ax in axs.ravel():
    ax.grid()
    ax.set_title('')
plt.suptitle(f'Monthly maxima in ERA5, lat: {lat}, lon: {lon}')
plt.show()
```

Monthly maxima in ERA5, lat: 60.5, lon: 25.0



GEV analysis

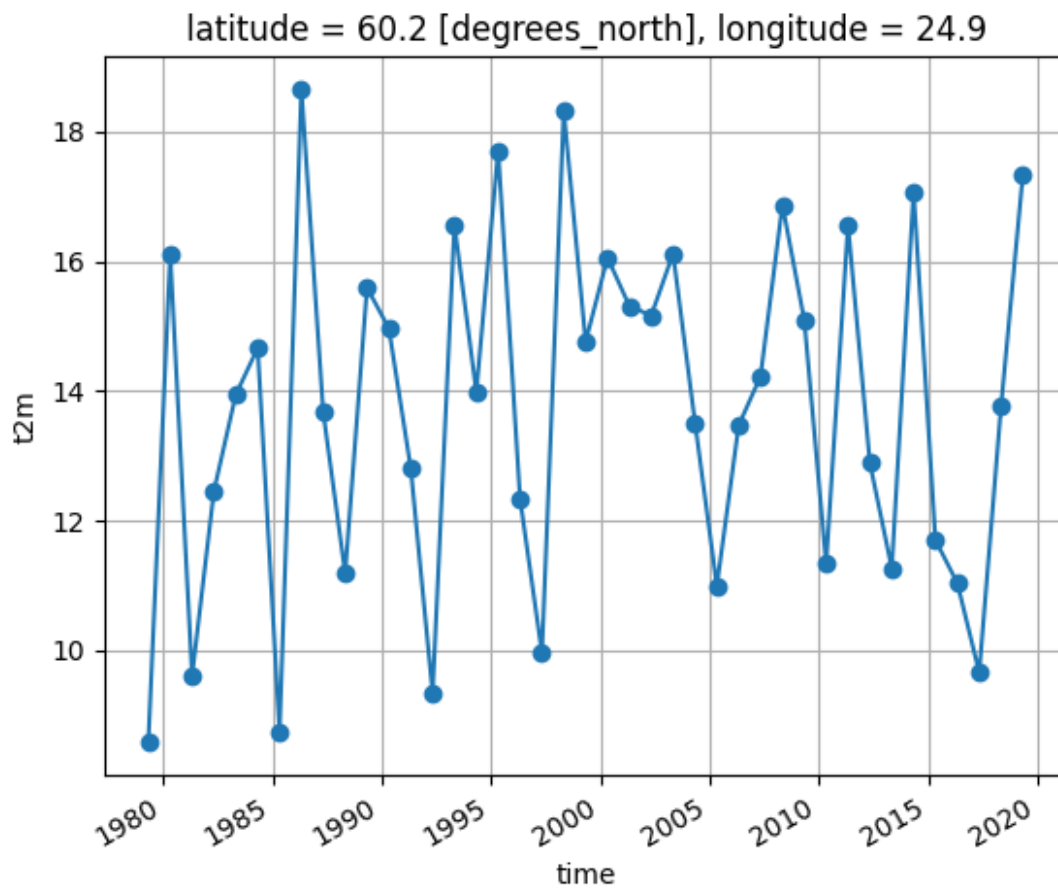
We provide a set of Python functions that to fit a generalized extreme value distribution to a time series data and calculate return levels for given return periods. It uses Stan probabilistic language to define the statistical model and calculate posterior probabilities for GEV parameters as well as for quantiles of the fitted distribution. These can be used to calculate return levels and their uncertainties. The estimation is based on Markov chain Monte Carlo (MCMC) sampling.

```
import cmdstan_gev as stangev

# select one location and one month
lat = 60.2
lon = 24.9
month = 4

months = era5['time.month']
y = era5['t2m'].where(months==month, drop=True).interp(latitude=lat, longitude=lon) - 273.15

y.plot(marker='o')
plt.grid()
plt.show()
```

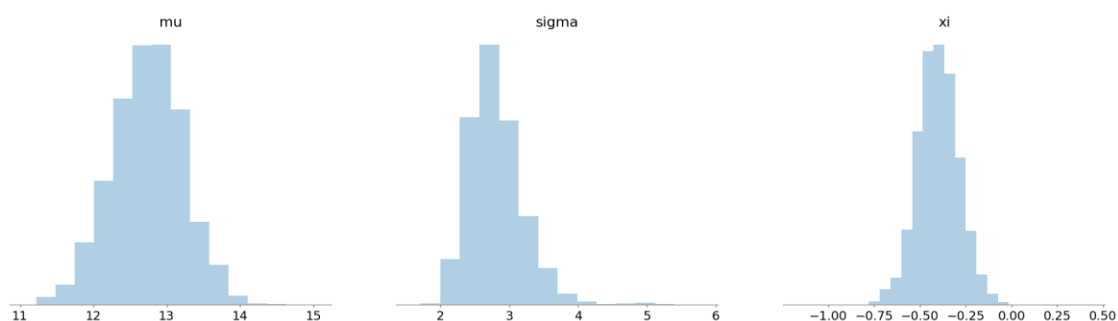


```
fit = stangev.gev_fit(y, hyper={'xi0': -0.3, 'xisig0': 0.2, 'sig0': 3.5},
                    adapt_delta=0.85, show_progress=False)
```

```
13:35:33 - cmdstanpy - INFO - CmdStan start processing
13:35:33 - cmdstanpy - INFO - CmdStan start processing
13:35:33 - cmdstanpy - INFO - CmdStan done processing
13:35:33 - cmdstanpy - WARNING - Some chains may have failed to converge.
Chain 1 had 157 divergent transitions (15.7%)
Chain 2 had 148 divergent transitions (14.8%)
Chain 3 had 208 divergent transitions (20.8%)
Chain 4 had 154 divergent transitions (15.4%)
Use function "diagnose()" to see further information.
```

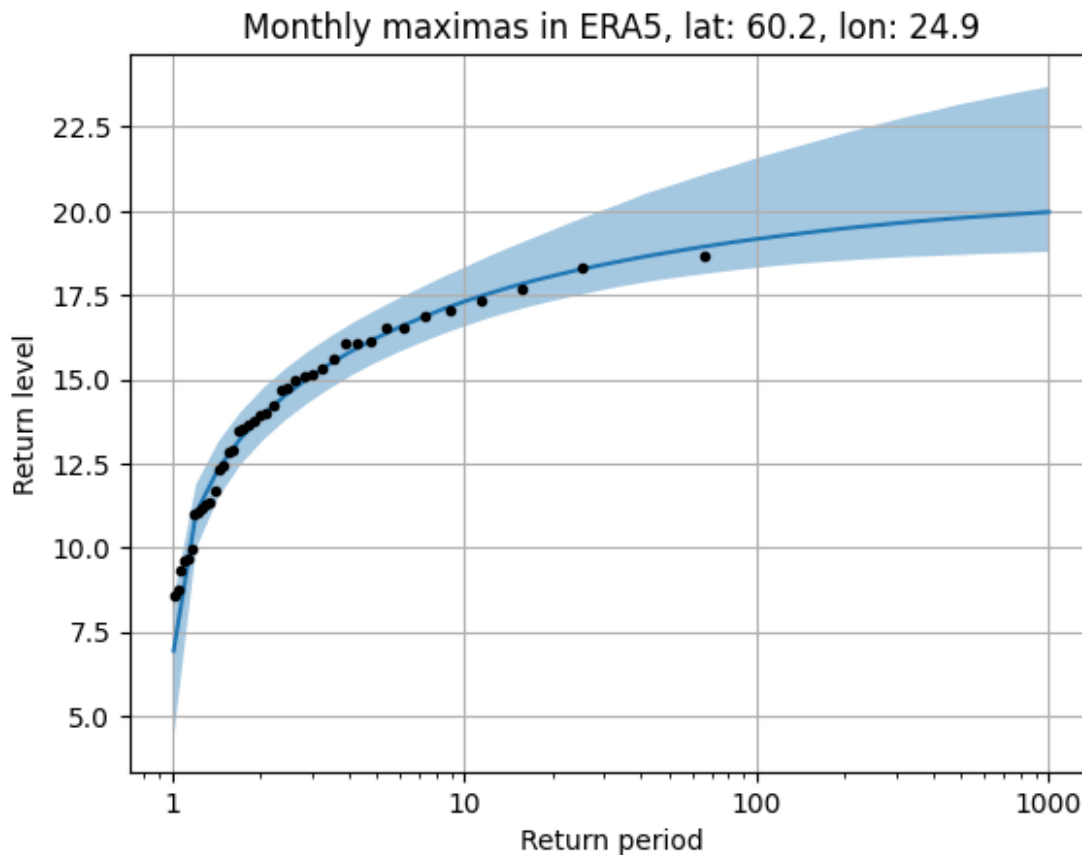
Plot chain histograms of estimated GEV parameters.

```
stangev.gev_posterior(fit)
plt.show()
```



Return level plot with return periods in logarithmic scale in the x axis. The blue shaded area gives 95% predictive uncertainty envelope for the return levels.

```
stangev.gev_qplot(y, fit, maxp=1000)
plt.title(f'Monthly maximas in ERA5, lat: {lat}, lon: {lon}')
plt.show()
```



Analysis on selected coordinates

We can calculate selected return periods for any pixel or collection of pixels in the ERA5 data. Below we select some locations that are studied in RISKADAPT project. The same analyses will be extended to the future climate in the next phase.

```
# lon, lat
locations = {
    'Trieste': [13.8, 45.63],
    'Lake Polyfytos Bridge': [21.973889, 40.232778],
    'Helsinki': [24.9375, 60.170833],
    'Kontiolahti': [30.0, 62.8],
}

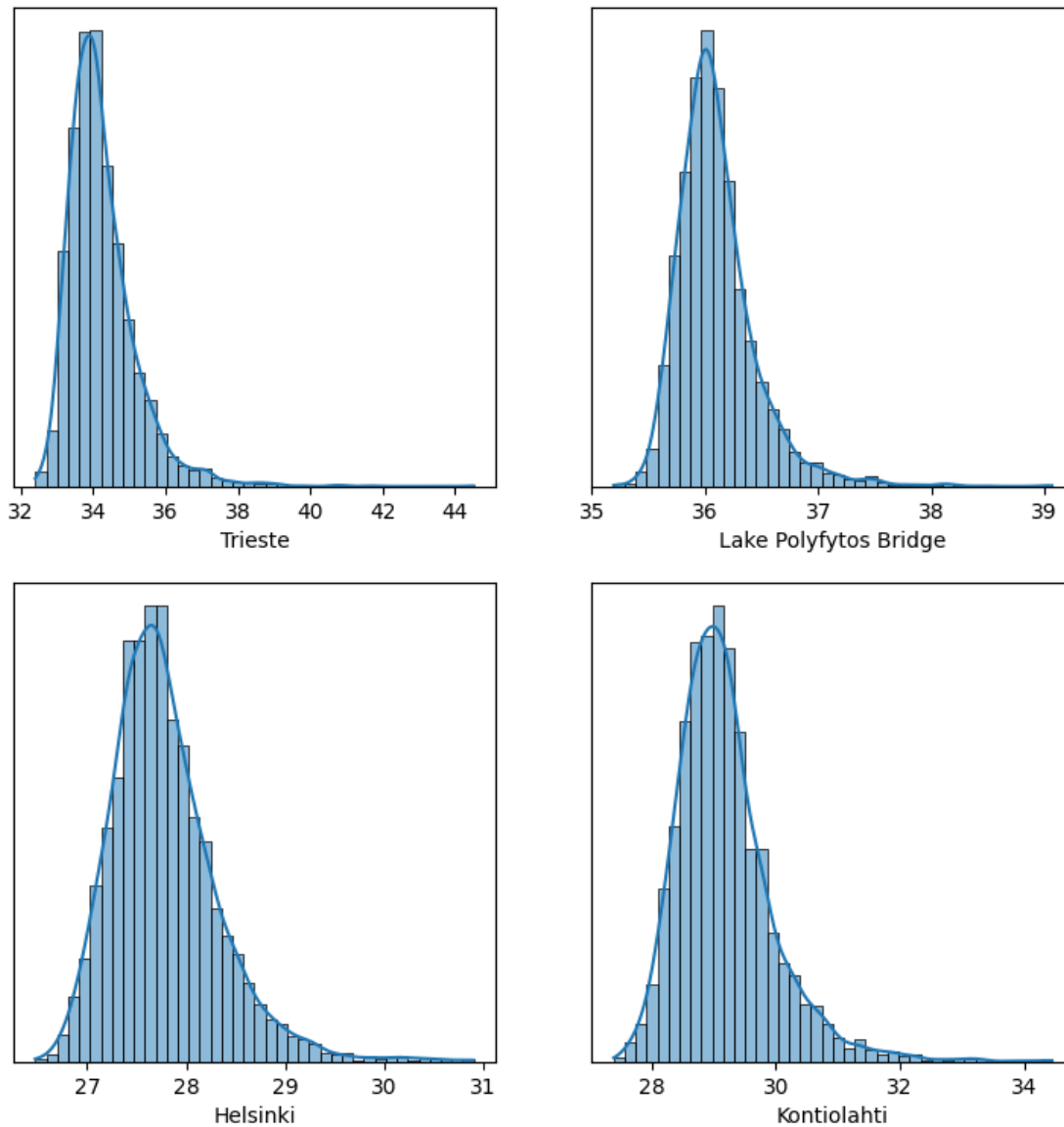
return_periods = [20]
month = 8

fig, axs = plt.subplots(2,2, figsize=(9, 9))

for i, l in enumerate(locations):
    ax = axs.ravel()[i]
```

```
lon, lat = locations[1]
y = era5['t2m'].interp(latitude=lat, longitude=lon).where(era5['time.month']
==month, drop=True) - 273.15
fit = stangev.gev_fit(y, quiet=True, show_progress=False)
r1_chain = stangev.gev_qpred(fit, yt = return_periods, return_chain=True)
sns.histplot(r1_chain.values[:,0], bins=40, kde=True, stat='probability', ax=ax)
ax.set_xlabel(f'{1}')
ax.set_ylabel('')
ax.set_yticks([])
plt.suptitle((f'{calendar.month_name[month]} temperature maximum [°C], '
f'\n with return period of {return_periods[0]} years.'
'\nCurrent climate'))
#axs[1,1].set_axis_off()
plt.show()
```


August temperature maximum [°C],
with return period of 20 years.
Current climate



The plots above show probability distributions of the estimated return levels of monthly maximum temperature in selected locations based on ERA5 monthly maxima. The figures show 20-year return period, so the estimated probability density for the maximum temperature to be observed at most every 20 years assuming the that climate stays the same as it has been during the years 1980-2019.

Annex 2. ERA5 Land examples

Here we demonstrate the use of ERA5 Land data from the Copernicus service.

We provide a script `era5land_download.py` to download the data for one location and month over years 1980-2019.

Below, we use two locations related to RISKADAPT Pilots, Lake Polyfytos Bridge in Greece and Cattinara Hospital in Italy.

```
import os
import numpy as np
import xarray as xr

import matplotlib.pyplot as plt

from glob import glob

DATA = os.path.expanduser('~'/DATA/RISKADAPT/')

locations = {
    'Lake Polyfytos Bridge': [21.973889, 40.232778],
    'Cattinara Hospital Trieste': [13.826012, 45.634376],
}
```

Extreme precipitation at Lake Polyfytos

First, we study extreme precipitation near Lake Polyfytos Bridge that is the subject of study in RISKADAPT Pilot 1. Data for August precipitation for years 1980-2019 have been downloaded with the utility `era5land_download.py`.

```
file = DATA+'era5_land_1980-2019_August_tp_Polyfytos.nc'
ds = xr.open_dataset(file)
ds

<xarray.Dataset>
Dimensions:      (time: 1280, step: 24, latitude: 2, longitude: 2)
Coordinates:
  number         int64 ...
  * time          (time) datetime64[ns] 1980-07-31 1980-08-01 ... 2019-08-31
  * step          (step) timedelta64[ns] 01:00:00 02:00:00 ... 1 days 00:00:00
  surface        float64 ...
  * latitude      (latitude) float64 40.3 40.2
  * longitude     (longitude) float64 21.9 22.0
  valid_time     (time, step) datetime64[ns] ...
Data variables:
  tp              (time, step, latitude, longitude) float32 ...
Attributes:
  GRIB_edition:      1
  GRIB_centre:       ecmf
  GRIB_centreDescription: European Centre for Medium-Range Weather Forecasts
  GRIB_subCentre:    0
  Conventions:       CF-1.7
```

```

institution:      European Centre for Medium-Range Weather Fore
casts
history:         2023-10-08T09:01 GRIB to CDM+CF via cfgrib-0.
9.1...

```

The variable `tp` has total precipitation cumulated hourly, separately for each day. The unit is meters. We interpolate to given location and adjust the coordinates for easier processing.

```

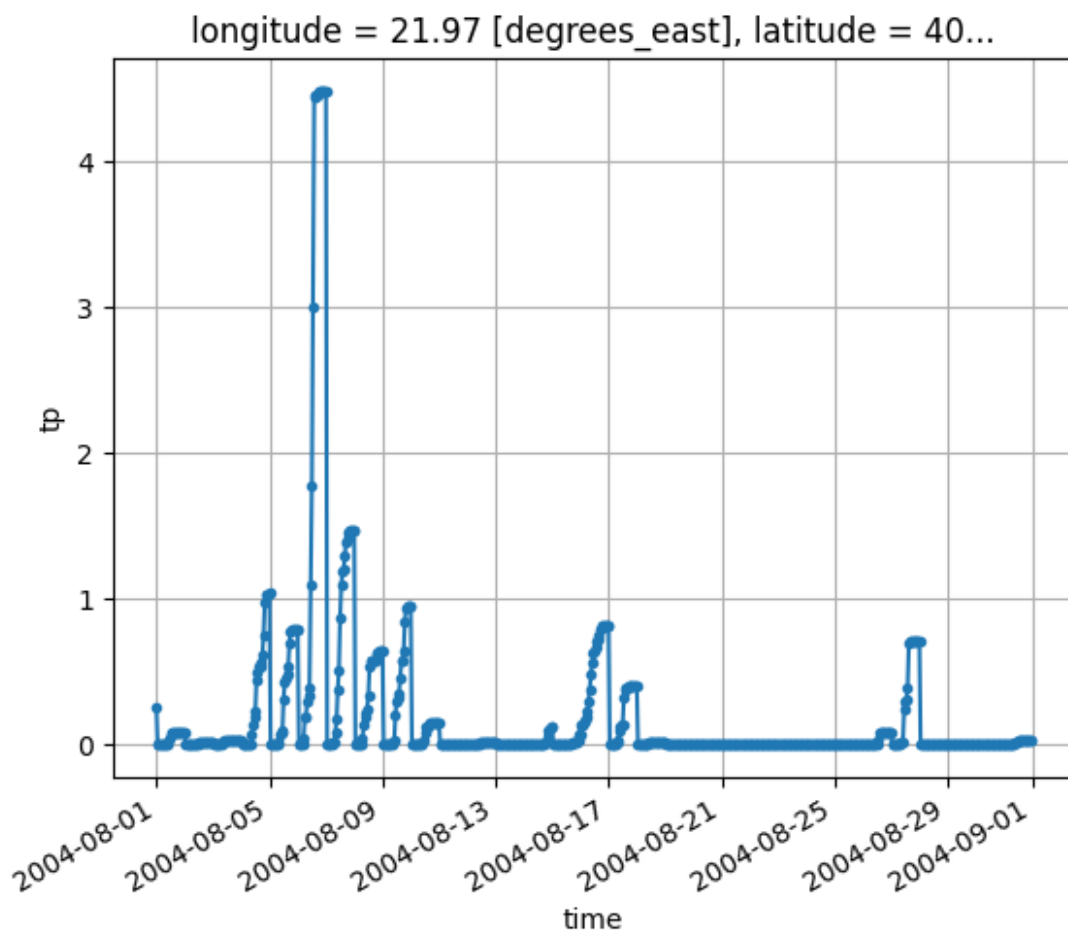
lon, lat = locations['Lake Polyfytos Bridge']
tp = ds['tp'].interp(longitude=lon, latitude=lat)

tp = (tp.stack(z=('time', 'step')).
      swap_dims({'z': 'valid_time'}).
      drop(['z', 'number', 'surface', 'time', 'step']).
      rename({'valid_time': 'time'}))
tp

<xarray.DataArray 'tp' (time: 30720)>
array([[          nan,           nan,           nan, ...,  1.29357e-05,
         1.29357e-05,           nan])
Coordinates:
  * time          (time) datetime64[ns] 1980-07-31T01:00:00 ... 2019-09-01
  longitude      float64 21.97
  latitude       float64 40.23
Attributes: (12/30)
  GRIB_paramId:          228
  GRIB_dataType:         fc
  GRIB_numberOfPoints:   4
  GRIB_typeOfLevel:      surface
  GRIB_stepUnits:        1
  GRIB_stepType:         accum
  ...
  GRIB_shortName:        tp
  GRIB_totalNumber:      0
  GRIB_units:            m
  long_name:             Total precipitation
  units:                 m
  standard_name:         unknown

(tp.where(tp['time.year']==2004)*1000).plot(marker='.')
plt.grid()
plt.show()

```



Sum the daily values for the selected month for each year and then take 24 hour differences to get *tp24*, which is the total precipitation for each previous 24 hours. Transform *m* to *mm*.

```
tp24 = tp.groupby(tp['time.year']).cumsum() * 1000
tp24.name = 'tp24'
```

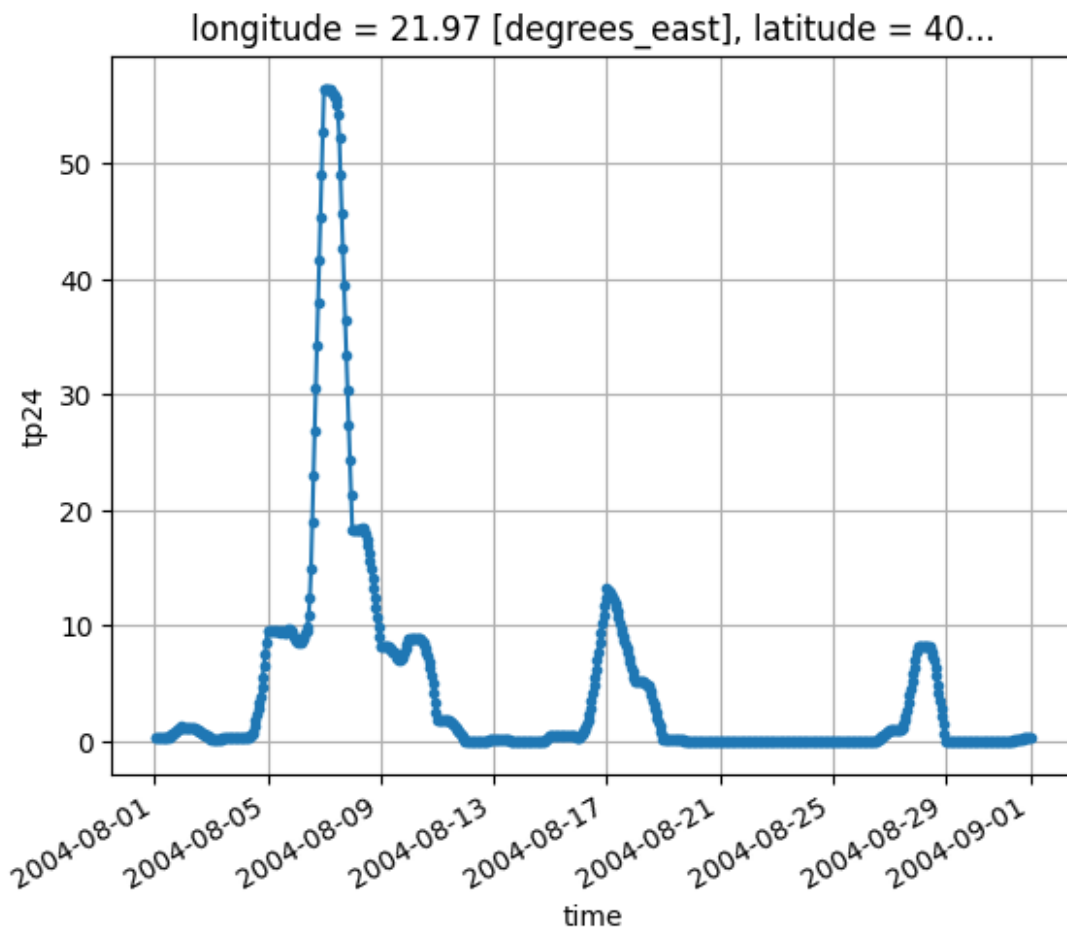
```
def tp24fun(ds):
    time1 = ds.time[ds.time >= ds.time[0] + np.timedelta64(24, 'h')]
    time2 = time1 - np.timedelta64(24, 'h')
    out = xr.full_like(ds, fill_value=np.nan)
    out.loc[dict(time=time1)] = (ds.sel(time=time1).values -
                                ds.sel(time=time2).values)

    return out
```

```
tp24 = tp24.groupby(tp24['time.year']).map(tp24fun)
tp24
```

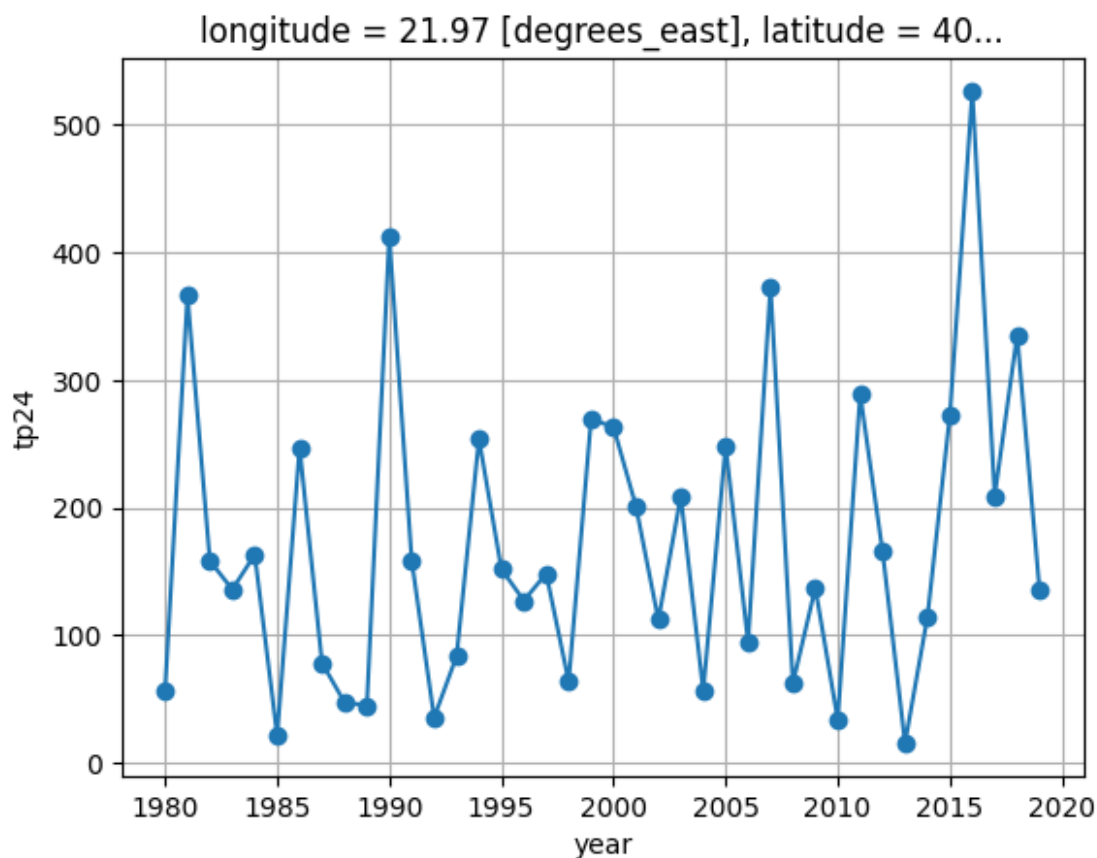
```
<xarray.DataArray 'tp24' (time: 30720)>
array([ nan,    nan,    nan, ...,  0.17789,  0.18867,  0.18651])
Coordinates:
  * time      (time) datetime64[ns] 1980-07-31T01:00:00 ... 2019-09-01
    longitude float64 21.97
    latitude  float64 40.23
```

```
tp24.where(tp24['time.year']==2004).plot(marker='.')  
plt.grid()  
plt.plot()  
[]
```



And then we can calculate the maximum 24 hour precipitation for each year for the selected month.

```
tp24.groupby('time.year').max().plot(marker='o')  
plt.grid()  
plt.show()
```



Now we could proceed to extreme value analysis.

Maximum wind speed near Cattinara Hospital

The next example calculates maximum 10 meter wind speed interpolated to the location of Cattinara hospital in Trieste, Italy. We study the August maximum 10 meter wind speed. ERA5 stores the wind as u and v components. First, we need to calculate 10 meter wind speed from those and do similar coordinate manipulations as for the tp above.

```
file = DATA+'era5_land_1980-2019_August_uv10_Trieste.nc'
ds = xr.open_dataset(file)
ds

<xarray.Dataset>
Dimensions:      (time: 1280, step: 24, latitude: 2, longitude: 2)
Coordinates:
  number         int64 ...
  * time         (time) datetime64[ns] 1980-07-31 1980-08-01 ... 2019-08-31
  * step        (step) timedelta64[ns] 01:00:00 02:00:00 ... 1 days 00:00:00
  surface       float64 ...
  * latitude    (latitude) float64 45.7 45.6
  * longitude   (longitude) float64 13.8 13.9
  valid_time    (time, step) datetime64[ns] ...
Data variables:
  u10           (time, step, latitude, longitude) float32 ...
  v10           (time, step, latitude, longitude) float32 ...
Attributes:
```

```

GRIB_edition:          1
GRIB_centre:          ecmf
GRIB_centreDescription: European Centre for Medium-Range Weather Fore
casts
GRIB_subCentre:       0
Conventions:          CF-1.7
institution:          European Centre for Medium-Range Weather Fore
casts
history:              2023-10-09T14:26 GRIB to CDM+CF via cfgrib-0.
9.1...

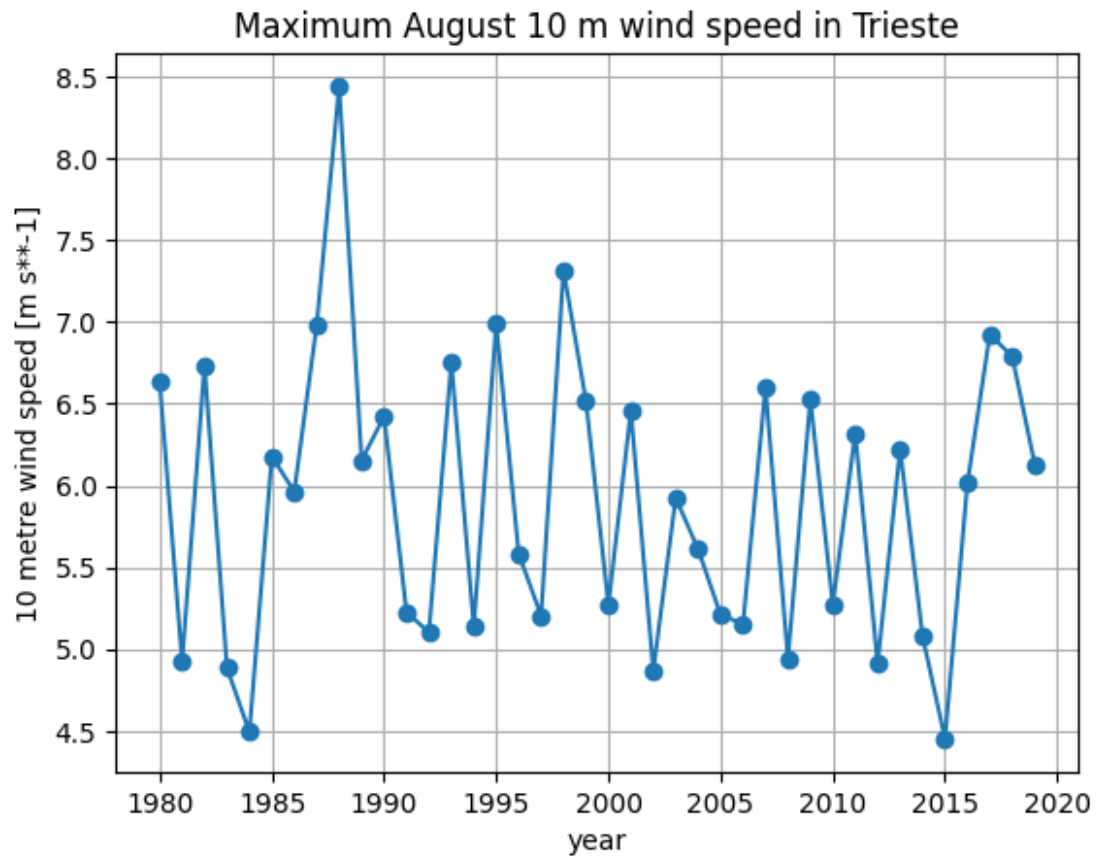
lon, lat = locations['Cattinara Hospital Trieste']
ds['ws10'] = np.sqrt(np.square(ds['u10']) + np.square(ds['v10']))
ds['ws10'].attrs = ds['u10'].attrs.copy()
ds['ws10'].attrs['long_name'] = '10 metre wind speed'
ws10 = ds['ws10'].interp(longitude=lon, latitude=lat).astype(np.float32)

ws10 = (ws10.stack(z=('time', 'step')).
        swap_dims({'z': 'valid_time'}).
        drop(['z', 'number', 'surface', 'time', 'step']).
        rename({'valid_time': 'time'}))
ws10

<xarray.DataArray 'ws10' (time: 30720)>
array([  nan,  nan,  nan, ...,  1.88802,  1.86969,  nan],
      dtype=float32)
Coordinates:
  * time      (time) datetime64[ns] 1980-07-31T01:00:00 ... 2019-09-01
    longitude float64 13.83
    latitude  float64 45.63
Attributes: (12/30)
  GRIB_paramId:          165
  GRIB_dataType:         fc
  GRIB_numberOfPoints:   4
  GRIB_typeOfLevel:      surface
  GRIB_stepUnits:        1
  GRIB_stepType:         instant
  ...
  GRIB_shortName:        10u
  GRIB_totalNumber:      0
  GRIB_units:            m s**-1
  long_name:             10 metre wind speed
  units:                 m s**-1
  standard_name:         unknown

ws10.groupby('time.year').max().plot(marker='o')
plt.title('Maximum August 10 m wind speed in Trieste')
plt.grid()
plt.show()

```



Annex 3. GPEX data

This example uses Global Precipitation EXtremes dataset GPEX. This data was used for article: Extreme Precipitation Return Levels for Multiple Durations on a Global Scale, Gründemann et al., 2021. (<https://doi.org/10.1016/j.jhydrol.2023.129558>)

The data set *GPEX.nc* can be downloaded from: <https://opendap.4tu.nl/thredds/catalog/data2/fig/12764429/4/catalog.html>. The data file contains global estimates of extreme precipitation using four extreme value methods (GEV, POT, Gumbel and MEV) for eight durations (3 hours - 10 days).

See page at: https://data.4tu.nl/articles/_/12764429/4 for more details.

```
import numpy as np
import xarray as xr

import matplotlib.pyplot as plt

import geopandas as gpd
import regionmask
import cartopy.crs as ccrs
from cartopy.io.img_tiles import OSM

imagery = OSM(cache=True)

/usr/local/share/venvs/sci/lib/python3.10/site-packages/cartopy/io/img_tiles.py:113: UserWarning: Cartopy created the following directory to cache GoogleWTS tiles: /var/folders/8l/qwchy9rd09x6v46zs3_zbmxm0000gn/T/cartopy_cache_dir/OSM
  warnings.warn(
```

Open downloaded data set. The spatial resolution is 0.1°.

```
ds = xr.open_dataset('~/.DATA/GPEX/GPEX.nc')
ds

<xarray.Dataset>
Dimensions:                (lat: 1480, lon: 3600, dur: 8, tr: 10, year: 38)
Coordinates:
  * lat                     (lat) float32 89.95 89.85 89.75 ... -57.75 -57.85
                             -57.95
  * lon                     (lon) float64 -179.9 -179.9 -179.8 ... 179.8 179.9
                             179.9
  * dur                     (dur) int32 3 6 12 24 48 72 120 240
  * tr                      (tr) int32 2 5 10 20 39 50 100 200 500 1000
  * year                    (year) int32 0 1 2 3 4 5 6 7 ... 30 31 32 33 34 35
                             36 37
Data variables: (12/26)
  gev_estimate              (lat, lon, dur, tr) float32 ...
  pot_estimate              (lat, lon, dur, tr) float32 ...
  mev_estimate              (lat, lon, dur, tr) float32 ...
  gumbel_estimate           (lat, lon, dur, tr) float32 ...
  observed_estimate         (lat, lon, dur, tr) float32 ...
  gev_location              (lat, lon, dur) float32 ...
  ...                       ...
  gumbel_location           (lat, lon, dur) float32 ...
```

```

gumbel_scale      (lat, lon, dur) float32 ...
annual_maximum   (lat, lon, dur, year) float32 ...
hydroyear        (lat, lon) float32 ...
running_parameter (lat, lon) timedelta64[ns] ...
mask             (lat, lon) uint8 ...
Attributes:
  title:          GPEX
  description:    Global Precipitation EXtremes dataset. This data was
use...
  acknowledgment: Contains modified Multi-Source Weighted-Ensemble Prec
ipi...
  authors:        Gaby Gründemann, Enrico Zorzetto, Hylke Beck, Marc Sc
hle...
  date_created:   2021-08-25
  creator_name:   Gaby Gründemann
  creator_email:  g.j.gruendemann@tudelft.nl
  institution:    Department of Water Management, Faculty of Civil Engi
nee...
  conventions:    CF 1.7

```

For illustration, we use a shape file for Haliacmon river drainage basin and select a rectangular area around the basin.

```

shape = gpd.read_file('Drainage_basin/basin.shp')
bb = shape.to_crs('EPSG:4326').bounds.values[0]

bb = bb + [-0.1, -0.1, 0.1, 0.1]
ds2 = ds.sel(lon=slice(bb[0], bb[2]), lat=slice(bb[3], bb[1]))

shape.to_crs('EPSG:4326').bounds

```

	minx	miny	maxx	maxy
0	20.776522	39.818271	21.959666	40.809015

Plot with a background map.

```

tr = 50
dur = 6

p0 = imagery.crs
p1 = ccrs.PlateCarree()

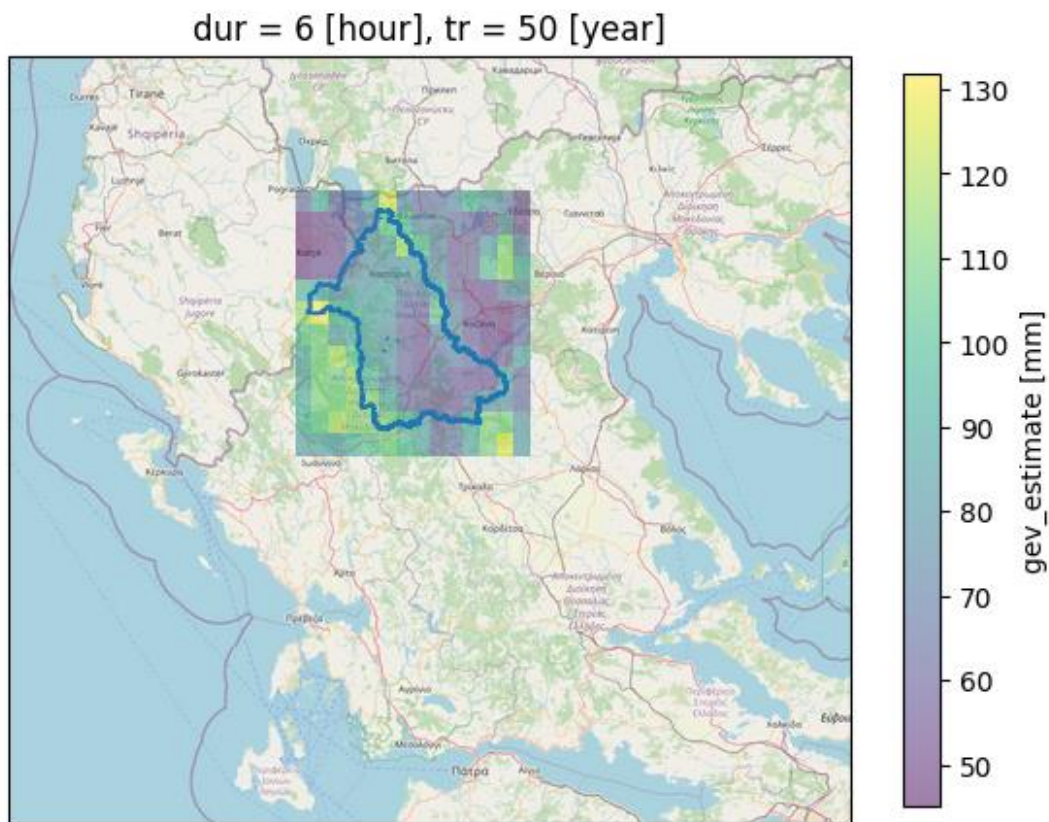
fig, ax = plt.subplots(1, 1, figsize=(7, 7), subplot_kw={'projection': p0
})
ax.set_extent(np.r_[19.0, 24.0, 38, 41.5], crs=p1)

ax.add_image(imagery, 8, interpolation='spline36')
shape.to_crs(p1).boundary.plot(ax=ax, transform=p1)

gev = ds2['gev_estimate'].sel(tr=tr, dur=dur)
m = gev.plot.pcolormesh(x='lon', y='lat',
                        transform=p1, ax=ax, alpha=0.5,
                        cbar_kwargs={'shrink': 0.7})

plt.show()

```



Plot one return period for several event durations, dur [h].

tr = 50

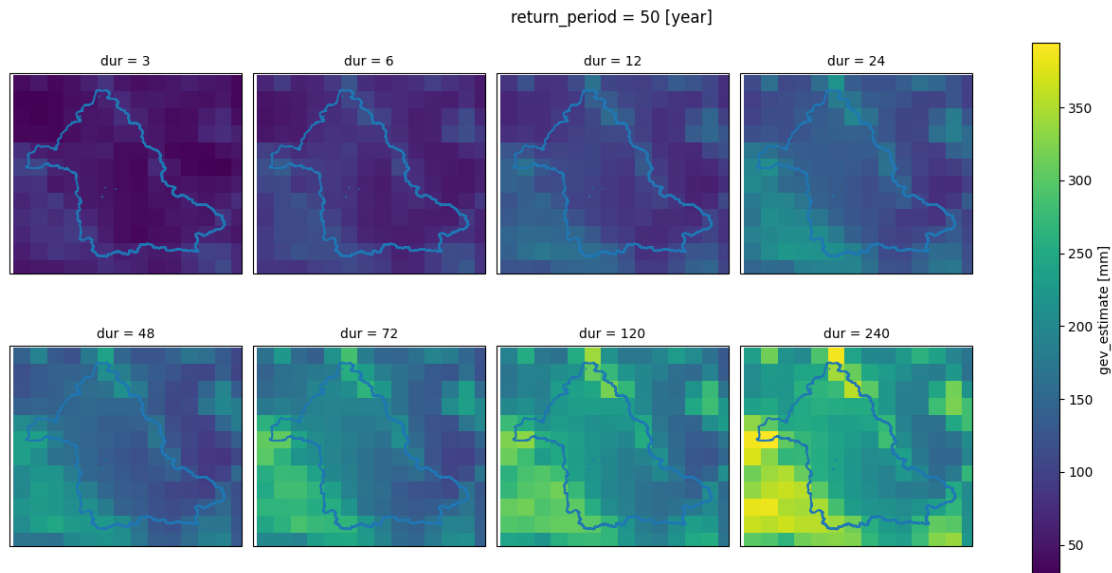
```

gev = ds2['gev_estimate'].sel(tr=tr)
m = gev.plot.pcolormesh(x='lon', y='lat', col='dur', col_wrap=4,
                       transform=p1,
                       subplot_kws={'projection': p1})
plt.suptitle(f'{gev.tr.attrs.get("long_name")} = {gev.tr.values} [{gev.tr.attrs.get("units")}]', y=1.02)

for ax in m.axes.ravel():
    ax.set_extent(np.r_[bb[0], bb[2], bb[1], bb[3]], crs=p1)
    shape.to_crs(p1).boundary.plot(ax=ax, transform=p1)

plt.show()

```

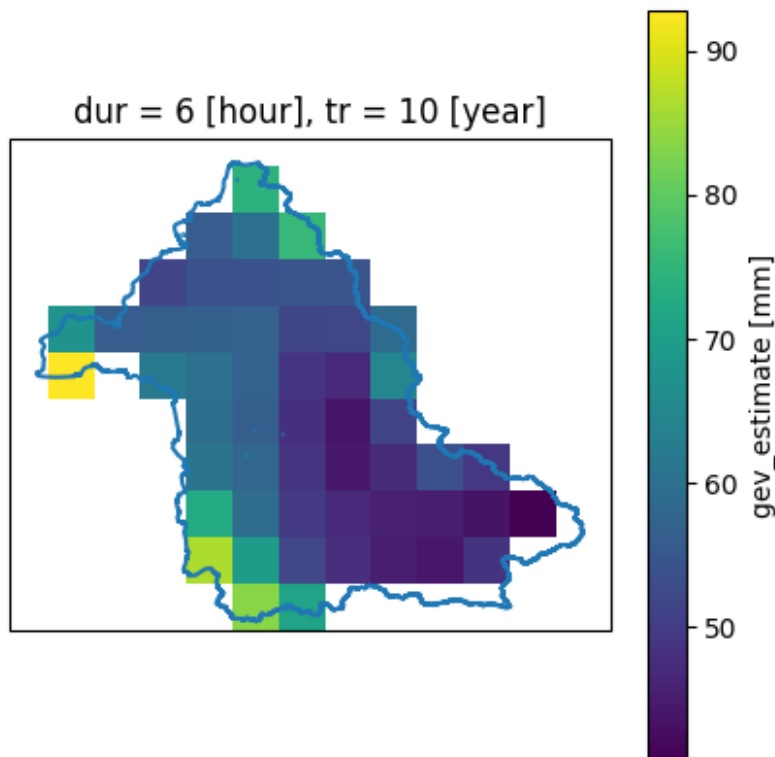


IDF intensity - duration - frequency curves

IDF curves can be used for various hydrological analyses. In GPEX data, intensity is calculated from precipitation and duration. The data has 10 return periods from 2 to 1000 years. Below, we mask the data to select only pixels for Heliacmon river basin. Then we calculate average IDF curves over the areas for all provided return periods.

```
mask = regionmask.mask_geopandas(shape.to_crs('EPSG:4326'),
                                  ds['lat'].values,
                                  ds['lat'].values,
                                  lon_name='lon', lat_name='lat')

fig, ax = plt.subplots(1, 1, figsize=(5, 5), subplot_kw={'projection': p1
})
ds['gev_estimate'].sel(tr=10, dur=6).where(mask==0, drop=True).plot(transform=p1)
shape.to_crs(p1).boundary.plot(ax=ax, transform=p1)
plt.show()
```



```
plt.figure(figsize=(10, 5))

gevmean = ds['gev_estimate'].where(mask==0, drop=True).mean(dim=['lon', 'lat'])
(gevmean / gevmean['dur']).plot.line(x='dur')
plt.ylabel('intensity [mm / h]')
plt.grid()
plt.title('IDF plot for Haliacmon river drainage basin')
plt.show()
```

