Manual Climate Explorer Steps

Formatting legend

Make sure to use consistent formatting in this document.

Text that refers to a clickable button in the Climate Explorer should be underlined, e.g. Daily fields.

Text that refers to **tool options** should be **bold**.

Text that refers to *headings* or *any other non-clickable text* should be *italic*.

Text that refers to “anything that should be typed” into the Climate Explorer should be in “quotation marks”.

1. A numbered list should be used for stepwise instructions
    a. And it should have sub-entries like this

Use BOLD letters for emphasis.

When referring to external documents use blue underlined text, and/or add a link to the document using the link option (ctrl+K).

Symbol	Description	Example
→	Directing the reader to a specific place or tool in the CE. To be used on stead of “see xx”, “under xx” or “go to xx”.	Choose an appropriate colormap → *Colours*

If necessary coloured text can be used (No standard yet).

Note that external documents such as the ‘results spreadsheet’ are not linked to this document. Instead, when this spreadsheet is mentioned, make sure you have your own document (table and/or text) where you save the results.

Climate Explorer attribution manual

Step by step instructions following the attribution protocol

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Introduction

The following document is a practical guide on how to use the Climate Explorer (CE) in an extreme event attribution study. This document is based on the WWA attribution protocol (Philip et al 2020 and Van Oldenborgh et al 2021) and is intended as a supplementary. Before proceeding with an attribution analysis using this manual, please read the attribution protocol.

The aim of this document is to provide detailed step by step instructions on how to perform an attribution analysis with the CE. It consists of two main sections. The first describes generalised steps which can be used to analyse any event, but which may require adapting depending on the event type or variable. The second section consists of two examples, one heatwave and one extreme precipitation event attribution analysis. The examples are intended to show a typical way of attributing the two types of events, but keep in mind that each extreme event has its own characteristics that may require adaptations or additional steps.

From version 1.1 onwards, the comparison of climates is done by warming level, and no longer by year. For the examples, this will in sections require a total overhaul, which has not yet been implemented. Instead, alternative text in red colour had been added.

Generalised steps

General tips

- ALWAYS LOG IN. This way any datasets you generate will be remembered by the CE and will be available for 3 days after last use. Logging in is also required for certain functions like uploading your own data or when using the Synthesis tool.
- Uploaded, generated, manipulated or viewed time series or fields are generally automatically added to View, upload time series and View, upload your field. If not, it can be added manually:
    - → *Manipulate this time series* → *Make index* → Add to list

  Alternatively removed:
    - → *Manipulate this time series* → *Remove index* → Remove from list
- THE CLIMATE EXPLORER REMEMBERS THE SETTINGS/PARAMETERS YOU USE IN EACH TOOL. This is very convenient when repeating an analysis with the same parameters on different datasets or time series. However, it also means that it does not revert to default settings. Therefore you should ALWAYS make sure that the settings are correct before proceeding with the computation.
- Results from the Trend in return times of extremes tool: the HTML-table at the top of the results page in CE is also contained in the text file found under raw data in the second plot showing the distributions in for the two years compared.

Preparation

0.1. Go to https://climexp.knmi.nl/ and log in.
0.2. Prepare any files needed for the analysis, e.g. NetCDF files of observed or modelled variables.
   a. TIP FOR MODELLED VARIABLES: If possible, it is advisable to upload a time series (ensemble) of the variable from which the event variable will be calculated (e.g. daily precipitation, temperature), and then calculate the event variable in the CE. That way it is easier to quality check the data.
0.3. Upload any files you need for your analysis. E.g.:
   a. Modelled time series, e.g. with daily values or an annual block maxima time series.
   b. Modelled GMST

Step 1: Analysis trigger

Please refer to the WWA attribution protocol (Philip et al 2020 and Van Oldenborgh et al 2021)

Step 2: Event definition

Several points should be considered when choosing and defining the event definition and variable (please refer to the WWA attribution protocol (Philip et al 2020 and Van Oldenborgh et al 2021)). However, the CE is useful for plotting various maps, which help with the event definition:

2.1. Create a map of the event
   a. An event map could be useful in the event definition process, especially in defining the spatial extent of the event.
   b. An event map is also useful as a visual communication tool, and should include the locations of stations or the area analysed.
2.2. Create map of rank (usually only used for temperature events).
   a. Plot the rank of the event compared with other years → *Investigate this field* → Compute mean, s.d. or extremes
   b. Constrain the contours to only plot the top ranked events (e.g. 5,7, or 10).
2.3. Create a climatology map
   a. This map will be needed to compare the spatial pattern of the observed variable to the simulated variable from the climate model in Step 4.

Step 3: Observed probability and trend

3.1. Create a time series from field (use mask or box), select appropriate station, or upload the observation time series.
3.2. Save the seasonal cycle figure (generated automatically when time series is uploaded or selected).
3.3. Plot last N days leading up to and including the event with the *View last N days* tool.

3.4. Generate extreme time series: → *Create a lower resolution time series*

3.5. Plot 15-year running standard deviation (temperature events) or dispersion (precipitation events) with the running mean/s.d./skew/kurtosis tool.

3.6. Calculate trends in return times of extremes with the attribution tool (see the WWA attribution protocol (Philip et al 2020 and Van Oldenborgh et al 2021)):

   a. Select covariate series, usually **smoothed GMST**.

   b. → *Use*: Choose appropriate statistical distribution:

      i. Gauss - soft extremes with low return periods that are not in the tail.

      ii. GPD - tail of the distribution, magnitude of exceedance of a high/low threshold, summer mean temperatures, drought.

      iii. GEV - largest observation from a large sample: annual/seasonal maximum, block maximum.

   c. → *Assume*: Use shift (temperature events) or scale (precipitation events).

   d. → *Return time*: Input the event *year.*

   e. Determine dGMSTpast (dCovariatePast), i.e. difference between GMST (covariate) at time of event and pre-industrial GMST (covariate). dGMSTpast will usually be the negative value of the Global Warming Index at time of event The value is needed to calculate the observed probability ratio.

   f. → *Compare*: Input dGMSTpast

Step 4: Model validation

Only the steps for assessing the statistical properties of the model data are described here. Before proceeding the model should be evaluated against the additional criteria mentioned in the WWA attribution protocol (Philip et al 2020 and Van Oldenborgh et al 2021). If using station data, check that the model gridpoint captures the physics of the station location (e.g. land point and not sea point, flat not mountainous etc.).

If the model data is not available in the CE, it is also possible to upload the time series into CE. If you are using the second option proceed directly to Step 4.2.

4.1. Get time series from your model from the CE under *Select a field* → Attribution runs, or access your uploaded model time series under → View, upload your time series.

4.2. Create and upload time series of variable for your model over the chosen region as one .nc (or other accepted format) file to your climate explorer account

   a. This file should contain lon, lat, time and ensembles as the main coordinates Note: The order of the time and ensemble coordinates in the file is important

4.3. Upload model global mean surface temperature GMST time series, to be used as covariate to your CE account.

4.4. Qualitative validation of the model data

   a. Save plots of seasonal cycles and time series

      i. Click on View, upload your time series in climate explorer and choose time series file uploaded in step 1

   b. Check the model has high enough resolution to capture the event.

c. Check the spatial pattern of variable in the model matches observations by comparing the climatology map of observations with modelled values
d. Check the model captures the orography accurately (If relevant)

4.5. Examine running mean/standard deviation/kurtosis by choosing your model time series and clicking on Running mean/s.d./skew/curtosis
a. temperature: variability (s.d) relatively constant over time (no strong trend)?
b. precipitation: dispersion (s.d/mean) relatively constant over time (no strong trend)?

4.6. Find model parameters of variability and shape using CE
a. Select time series for event and click on Trends in return times of extremes
b. Use the same options as in Step 3.6.
c. → *Years:* constrain model time series to match the length of observed time series used in Step 3.
d. → *Bias correction*: input return time of event in observed climate (results from Step 3)
e. Compute the values (should be taken to table of results with parameters)

4.7. Add results from your model to table of results containing all observations and models (below is sample table)

4.8. Check whether the model parameters are within the uncertainty of the corresponding observation parameters.

model	seasonal cycle	spatial pattern	variability sigma/mu (uncertainty)	shape parameter ksi	conclusion
EC-Earth	good	good	0.240 (0.229... 0.251)	0.005 (-0.033... 0.044)	**yes**, best estimates within uncertainty. Only 1930-2050 constraint from variability)

Step 5: Model attribution

5.1. Repeat Step 4.6 for the chosen return period (in bias correction option) and year range specific to the attribution
a. Select time series for event and click on Trends in return times of extremes
b. Use the same options as in Step 3.6.
c. → *Years:* constrain model time series to end in Ynow.
d. → *Bias correction*: input return time of event in observed climate (results from Step 3)
e. Compute the values (should be taken to table of results with parameters)

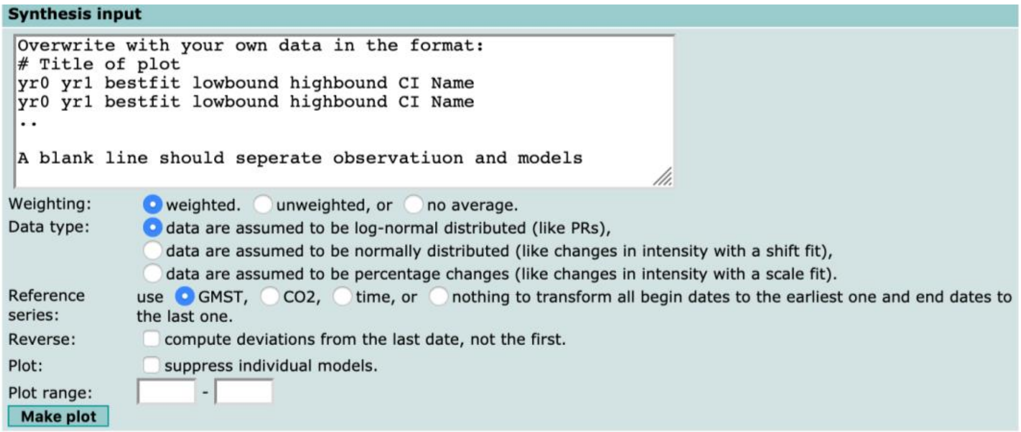
5.2. Add the results for probability ratio and change in intensity to the tables with their corresponding uncertainties

model	threshold for return period XX	Ynow (dGMST)	trend (uncertainty)	probability ratio PR (uncertainty)	change in intensity ΔI (uncertainty)

Step 6: Synthesis

The CE synthesis tool plots a figure containing both observational and model attribution results, and can additionally calculate an average. This average forms the basis of the attribution statement. Please refer to Otto et al 2024 for details on performing the synthesis and formulating an attribution statement.

6.1. Go to https://climexp.knmi.nl/synthesis.cgi and log in



6.2. Copy the results formatted for the Synthesis tool into the *Synthesis input* box from the results spreadsheet OR if there are not too many models you can write the results directly into the tool. If you choose the latter option, please adhere strictly to the following formatting:

a. The first line must start with a "#", followed by the plot title and any additional information you want to specify.
b. The following lines contain the observation and model results. A blank line must separate the observations and models, or else the tool reads all input as model results.
c. The results must contain the following entries, each separated by a blank space.
    i. *yr0*: year in the past
    ii. *yr1*: year now or in the future
    iii. *bestfit*: the best estimate of the variable, e.g. probability ratio or change in intensity
    iv. *lowbound*: lower uncertainty bound
    v. *highbound*: upper uncertainty bound
    vi. *CI*: confidence interval used to estimate the uncertainty bounds, normally set to "95" %
    vii. *Name:* label identifying dataset

6.3. The following options are available for calculating a synthesised value:

a. **weighted**:
b. **unweighted**:

c. **no average**: simply plots the values

6.4. Data type options:

a. The *log-normal distributed* option should be used when plotting and evaluating probability ratios.

b. The *normally distributed* option should be used when plotting intensity changes with shift (like temperature)

c. The *percentage changes* option should be used when plotting intensity changes with scale (like precipitation)

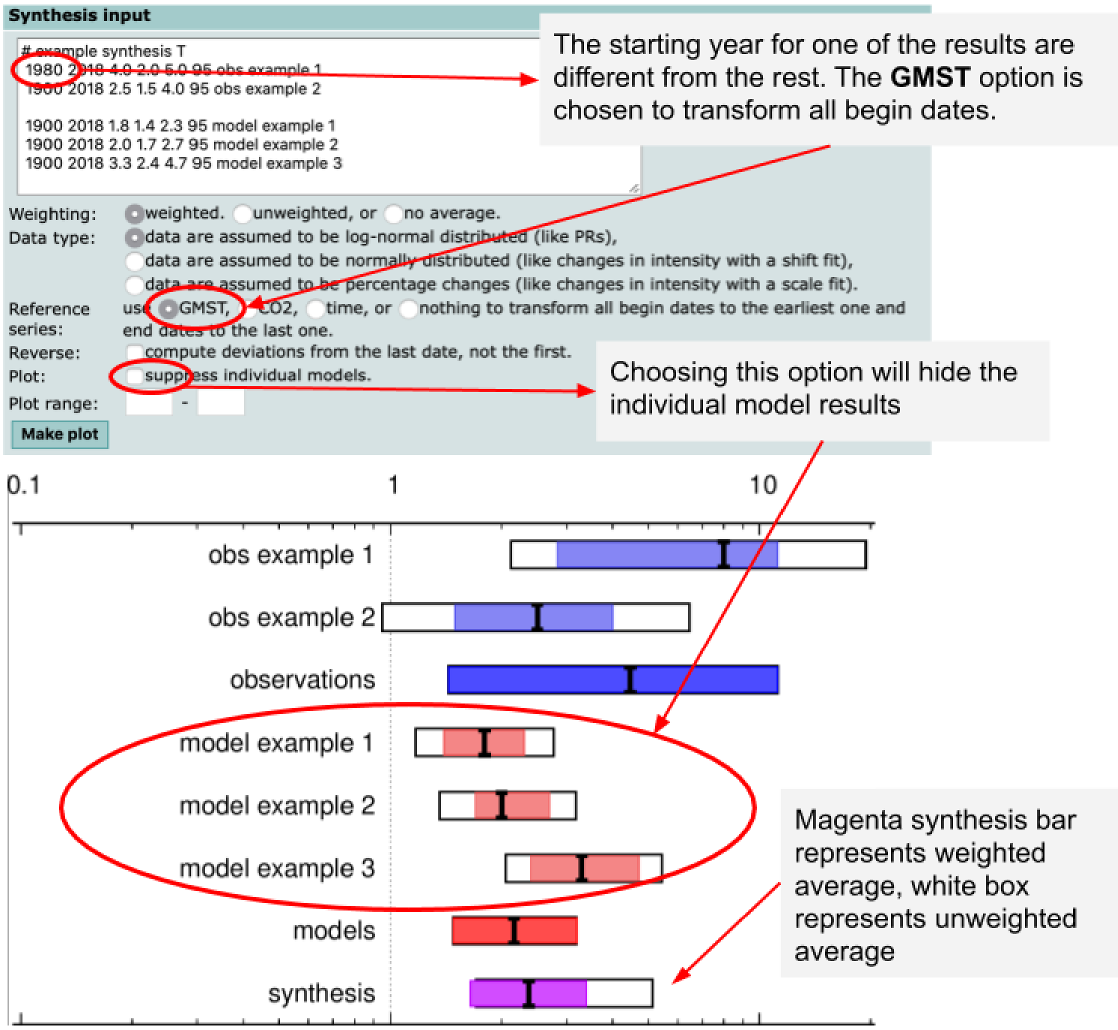
6.5. If the years compared are the same for all datasets, or if using warming levels, please select the **nothing to transform** option. For different starting years and GMST as covariate, select the **GMST** option.

6.6. For publishing purposes, if a lot of models are used in the synthesis, click **suppress individual models** to just show all observations, the *observations* synthesis bar, the *models* synthesis bar and the overall synthesis bar.

6.7. Sometimes it is necessary to adjust the *Plot range* so that all labels and intervals are properly displayed (especially with negative values, e.g. when plotting change in intensity).

6.8. Save the synthesis plot

6.9. Save the raw data as a text file. This contains the exact values for the average of observation, models and synthesis of both.



Examples

Temperature example: Heatwave summer 2018

Analysis of the 2018 European heatwave. Event variable TX3x (annual maximum of 3-day averaged maximum temperature). This example only shows the analysis for one of the locations used in the study.

Step 2: Event definition

Create a map of the event

2.1. Under *Select a field* on the right hand side choose Daily fields

2.2. Select variable: → *Reanalysis* → *ERA 1979-now 0.25° Europe* → *Tmax*

2.3. Calculate TX3x: → *Create a field with lower resolution*

   a. → *New time scale:* **annual (Jan-Dec)**

   b. → *New variable:* **max** *of Tmax*

   c. → *First apply:* “3” *-day running mean*

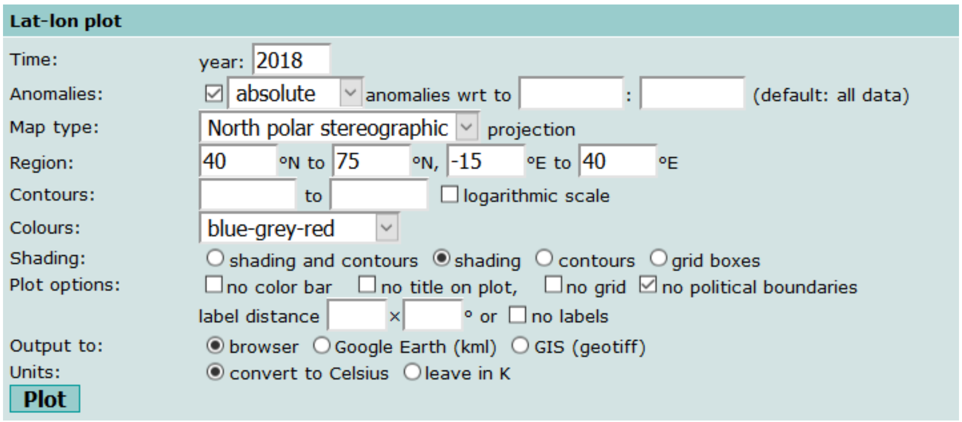
2.4. Make a map of TX3x for the event → Plot this field

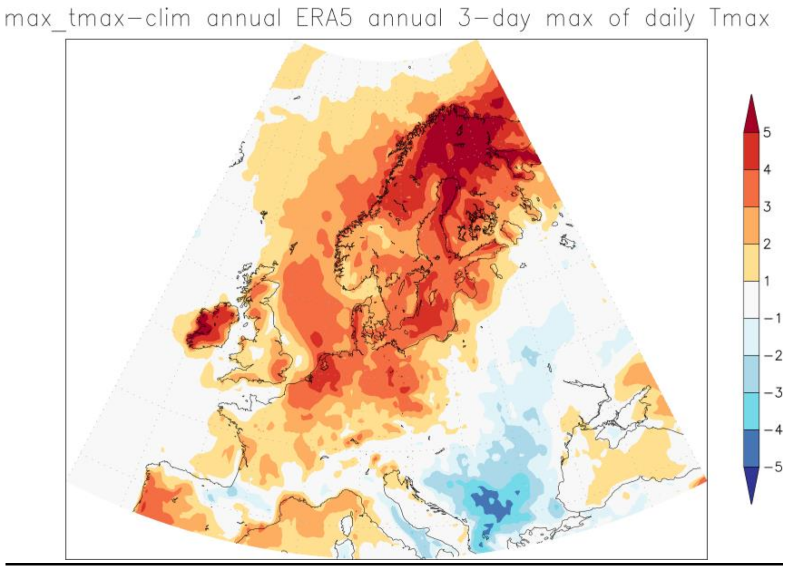
   a. → *Time:* Specify *year*: “2018”

   b. → *Anomalies:* **absolute** *anomalies*

   c. → *Map type:* **North polar stereographic**

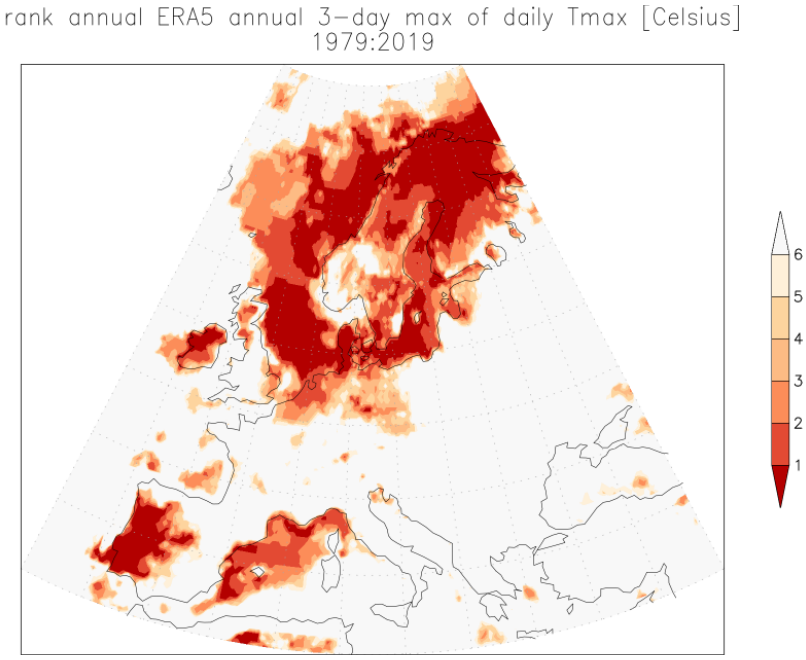
   d. → *Region*: “40” *°N to* “75” *°N,* “-15” *°E to* “40” *°E*





2.5. Plot rank of 2018 TX3x: → *Investigate this field* → Compute mean, s.d. or extremes

a. → *Property: Rank of year* "2018" *in the context of the other year*
b. *Map type* and *Region* same as Step 4 above
c. → *Colours*: ***red-grey***
d. → *Contours*: "1" *to* "6"
e. → *Years*: -"2019"



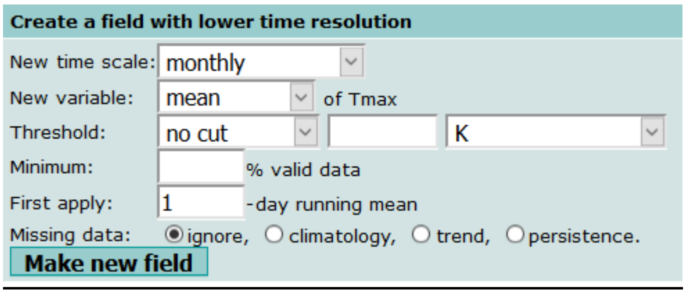
Average maximum temperature map for July 2018

2.6. Under *Select a field* on the right hand side choose Daily fields

2.7. Select variable: → ***Reanalysis*** → *ERA 1979-now 0.25° Europe* → *Tmax*

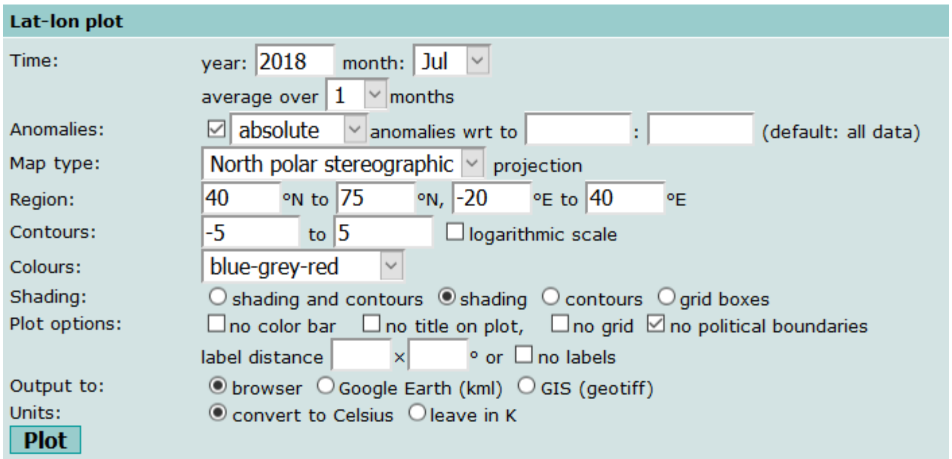
2.8. Create monthly means: → *Create a field with lower time resolution*

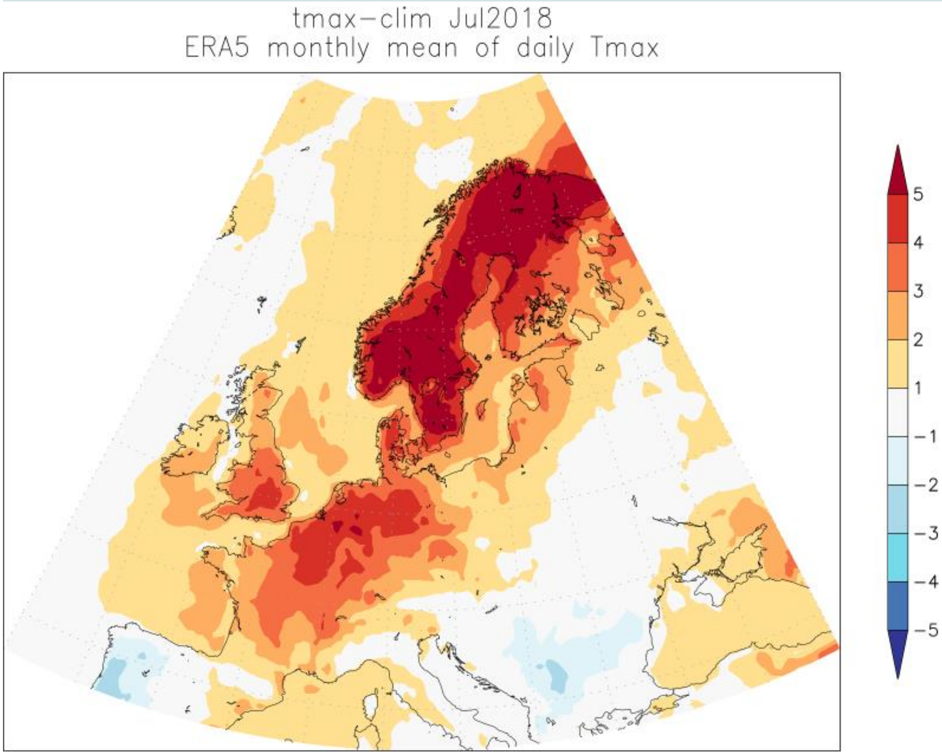
a. *New time scale:* **monthly**
b. *New variable:* **mean** *of Tmax*
c. → Make new field



2.9. → Plot this field

a. Select *year*: "2018" and *month*: **Jul**
b. Absolute anomalies





Create climatology map

This map will be needed to compare the spatial pattern of the variable to the modelled variable in Step 4.

2.10. Under *Select a field* on the right hand side choose Daily fields

2.11. Select variable: → *Reanalysis* → *ERA 1979-now 0.25° Europe* → *Tmax*

2.12. Create seasonal means: → *Create a field with lower time resolution*

a. → *New time scale:* **seasonal**

b. → *New variable:* **mean**

c. → Make new field

2.13. Plot climatology: → *Investigate this field* → Compute mean, s.d., or extremes

a. → *Property:* **mean**

b. → *Map type* and *Region* same as above

c. → *Contours*: "0" to "30"

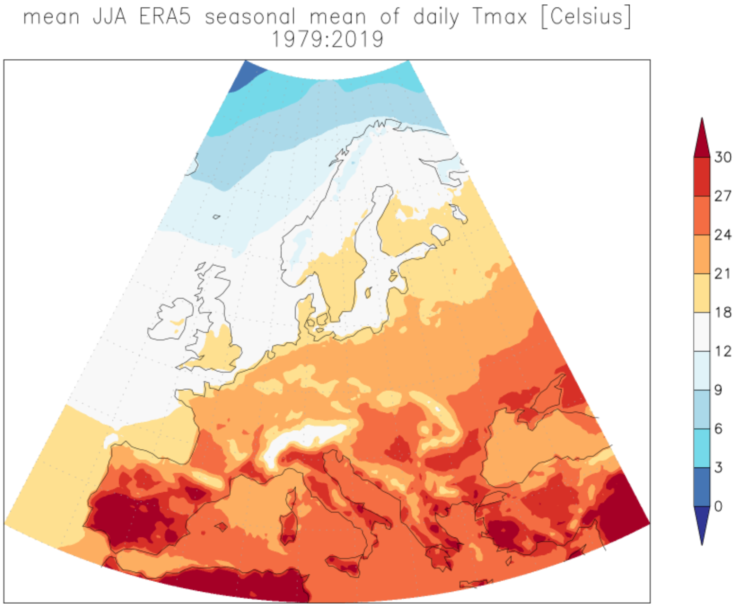
d. → *Colours*: **blue-grey-red**

e. → *Units*: **convert to Celsius**

f. → *Starting* *season*: **JJA**

g. → *Season:* **selecting** *over* **1** *seasons*

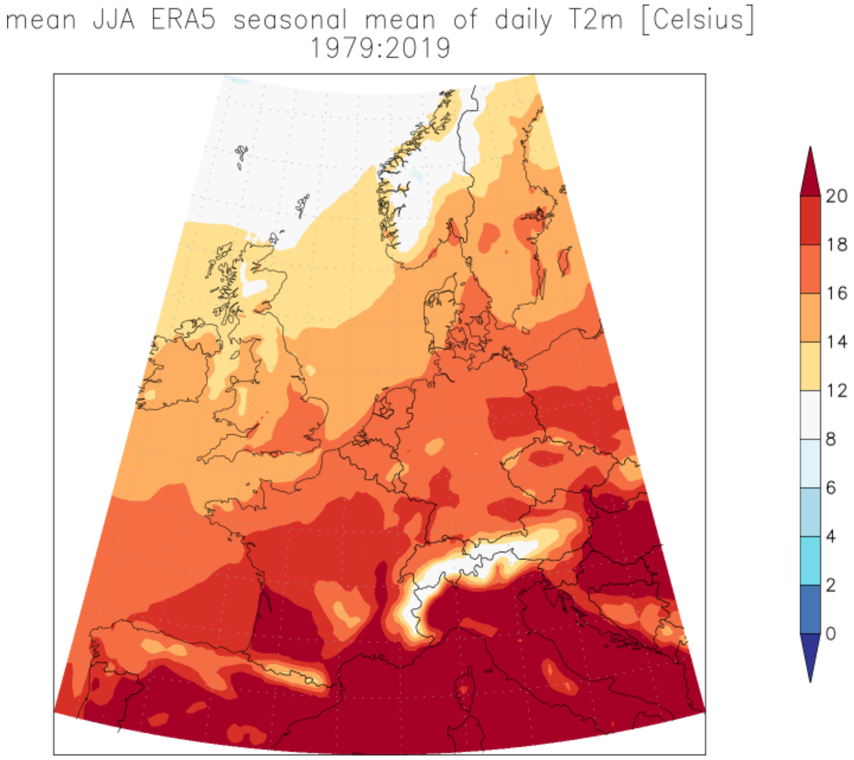
h. → *Years*: "" - "2019"



2.14. Repeat with mean daily temperature:

a. → *Contours*: "0" to "20"

b. → *Units*: **convert to Celsius**



Step 3: Observed probability and trend

Location: De Bilt, Netherlands (52.10N, 5.18E, 1.9m)

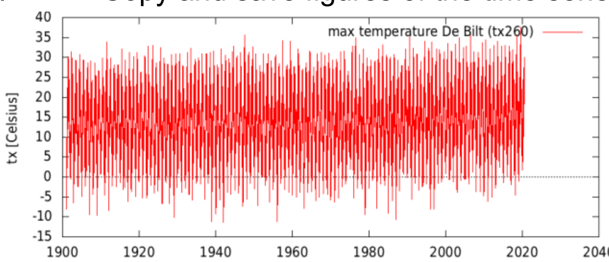
Get station data

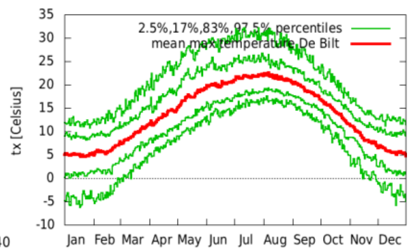
3.1. Select observational time series: → *Select a time series* → Daily station data → *Dutch daily data* → maximum temperature → *De Bilt (Netherlands)* → get data

OR

Upload your own time series: → *Select a time series* → View, upload your own time series

3.2. Copy and save figures of the time series and of the seasonal cycles





3.3. Quality checks (see Attribution protocol, Section 3 for further details):

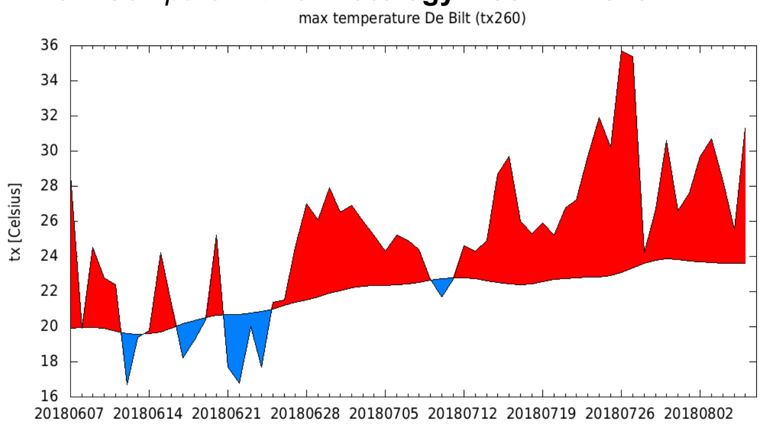
a. no urban or coastal station or mountain
b. no missing data or spurious trend
c. series is homogenised
d. no change in variability

3.4. Plot the day leading up to and including the event: → *Investigate this time series* → *View last* <u>30</u> *days*

a. → *Replot* “60” *days with end date* “2018” “08” “05”

b. → **observations**

c. *Compare with* **climatology** “1981” - “2010”



Calculate block maxima time series (TX3x)

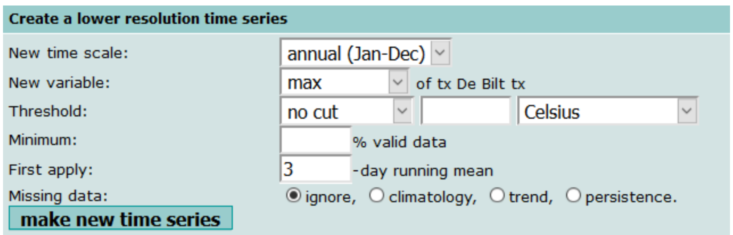
3.5. Go back to daily time series

3.6. Calculate TX3x: → *Create a lower resolution time series*

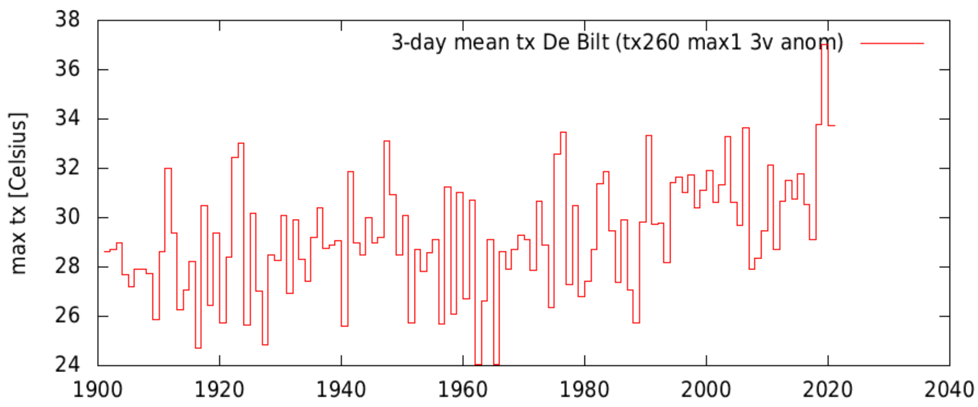
a. → *New time scale:* **annual (Jan-Dec)**

b. → *New variable:* **max** *of De Bilt tx*

c. → *First apply:* “3”-*day running mean*



d. → <u>make new time series</u>



Variability check

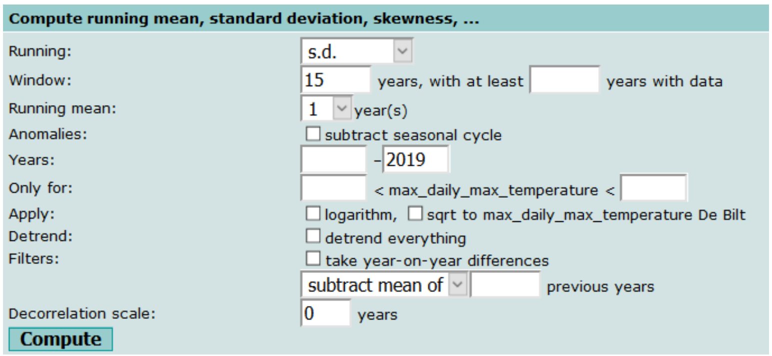
3.7. Check variability: → *Investigate this time series* → Running mean/s.d./skew/curtosis

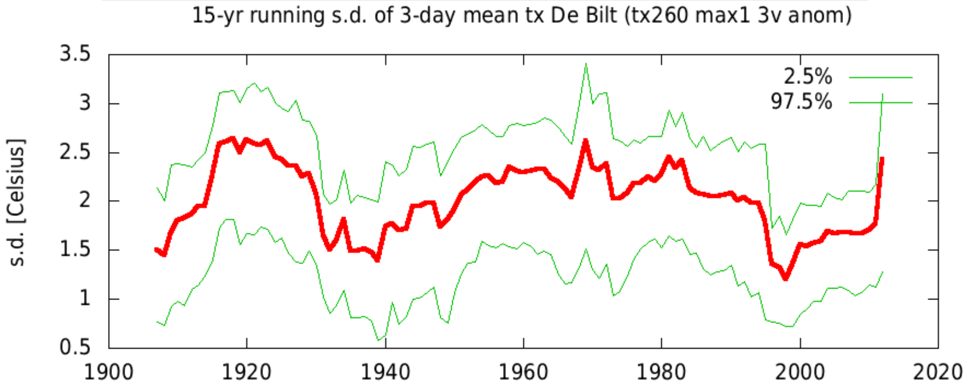
a. → *Running:* **s.d.**

b. → *Window:* “15” *years*

c. → *Years:* “” - “2019” [1]

d. → Compute





Fitting GEV distribution

3.8. Select observational time series: → *Select a time series* → Daily station data → *Dutch daily data* → maximum temperature → *De Bilt (Netherlands)* → get data

3.9. Go to the attribution tool: → *Investigate this time series* → Trends in return times of extremes

3.10. Select the covariate time series: → *Covariate series* → *System-defined annual timeseries* → **smoothed GMST**

3.11. Specify parameters to generate TX3x time series:

a. *Starting month:* **Jan**

b. *Season: selecting* **12** *month(s)*

c. *Running mean:* **3** *day(s)*

d. *Years:* “” - “2019”

[1] Excluding the year 2020 because records for this year are not complete at the time of writing.

e. *Use:* → **Block maxima** *and fig GEV using* **1** *yr blocks,* → **constrain shape to ±0.4** *of GEV only if no constraint does not work*

3.12. Specify parameters of attribution analysis:

a. *Assume: the PDF* **shifts** *with the covariate*, because the analysed event is a temperature event.

b. *Return time: year* "2018". The *choose to include it* box can be ticked in this case (always include the event to avoid a bias

c. *Compare: return time if it had occurred in year* "1900"

Compare: return time if it had at covariate value "-1.1" (for GMST2018-GMSTpast, see www.globalwarmingindex.org)

d. → Compute

Results

3.13. Save or copy a screenshot of the results table:

Jan-Dec 3-day ave De Bilt tx [Celsius] dependent on Global mean surface temperature (smoothed)			
parameter	**year**	**value**	**95% CI**
covariate:	1900	-0.16854	
	2018	0.94187	
N:		119	
Fitted to GEV distribution P(x) = exp(-(1+ξ(x-μ')/σ')^(-1/ξ))			
with μ'= μ+αT and σ' = σ and a Gaussian penalty on ξ of width 0.2			
μ':	1900	27.656	27.318... 28.066
σ':	1900	1.964	1.675... 2.174
μ':	2018	31.092	30.754... 31.502
σ':	2018	1.964	1.675... 2.174
ξ:		-0.227	-0.315... -0.133
α:		3.094	1.910... 4.213
return period event 2018 (value 33.767)	1900	222.45	73.417 ... 54366.
probability	1900	0.44953E-02	0.18394E-04 ... 0.13621E-01
return period event 2018 (value 33.767)	2018	5.6178	3.1574 ... 15.192
probability	2018	0.17801	0.65824E-01 ... 0.31672
probability ratio		39.598	9.6068 ... 6701.5
p-value probability ratio (one-sided)	≠ 1	0.0010	
change in intensity 1900-2018	diff	3.436	2.121 ... 4.679

3.14. Copy and paste values into results spreadsheet:

a. Ynow: *2018*

Event year: *2018*

b. Ypast: *1900*

Compare: return time if it had at covariate value "-1.1" (for GMST2018-GMSTpast, -1.2 for GMST2020-GMSTpast)

c. The 2018 event magnitude: *33.767* °C

d. Sigma σ': *1.964 (1.675 … 2.174)*

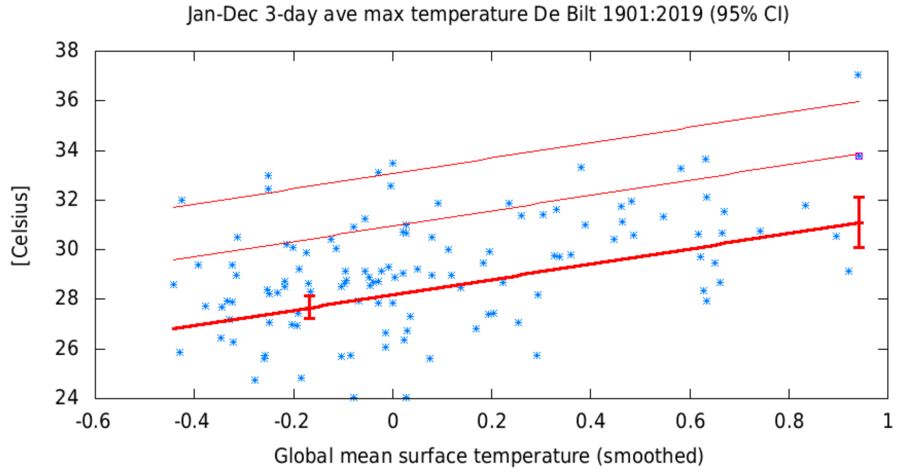
e. Shape ξ: *-0.227 (-0.315 … -0.133)*

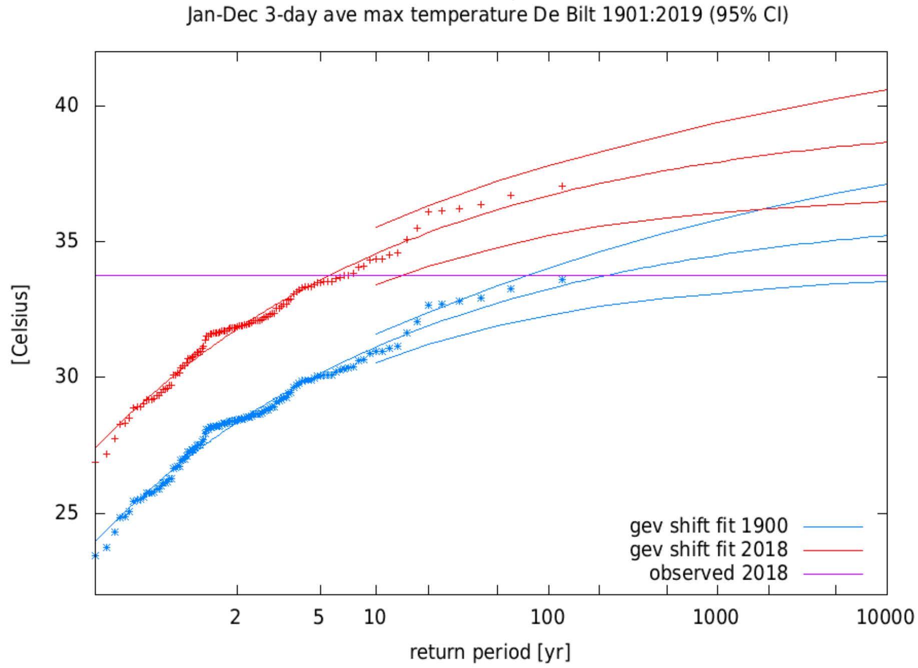
f. Return period of 2018 event (in 2018 climate): *5.6178 (3.1574 ... 15.192)* yr

g. Probability ratio: *39.598 (9.6068 … 6701.5)*

h. Change in intensity: *3.436 (2.121 ... 4.679)*

3.15. Save or copy figures. If figures are to be used later save as eps file.





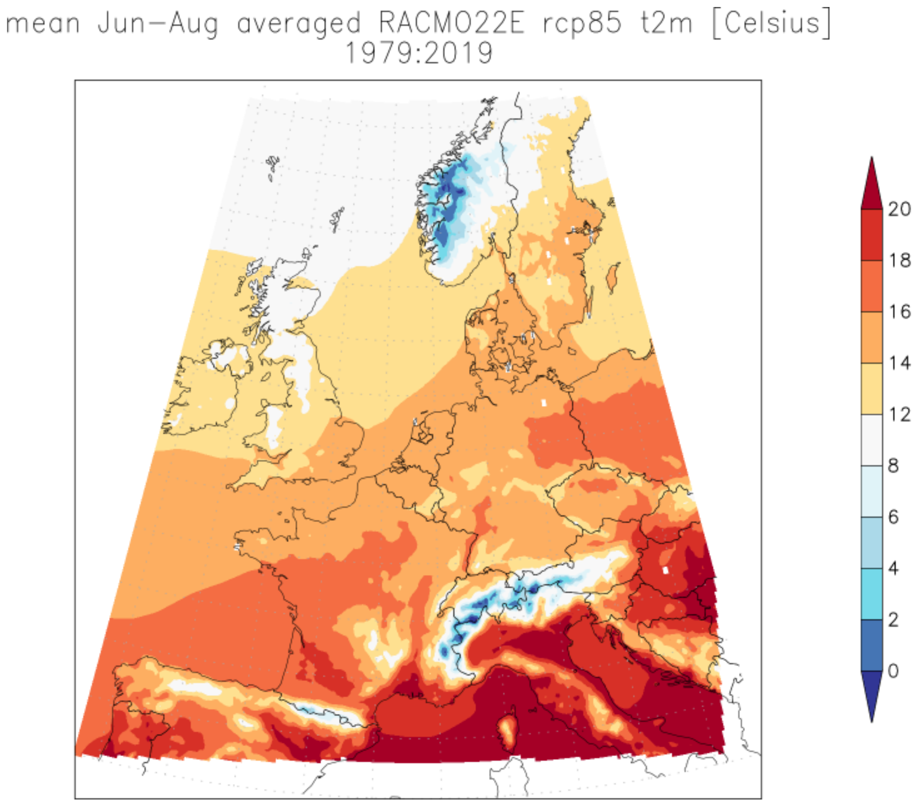
3.16. Save the values the figures are based by right clicking on raw data, and saving it as a .txt file. This is useful if you want to store the data or make your own figures. Additionally, the results table is contained in the text file attached to the event variable vs. return period plot (in HTML-format).

Step 4: Model validation

This example shows how to do the model validation for RACMO, which is available in the CE. If the model data is not available in the CE, it is also possible to upload the daily maximum temperature time series into the CE. If you are using the second option proceed directly to Check variability and seasonal cycle. However, do not forget to check the spatial pattern by generating a climatology field. This can also be uploaded and plotted by the climate explorer.

Spatial pattern

4.1. Reproduce the climatology map from Step 2?



Extract TX3x time series at station location

4.2. Select the TX3x time series for RACMO: → *Select a field* → Attribution runs → *RACMO 12km / EC-EARTH2.3 1950-2100* → *16 annual* → *RCP8.5* → *TX3x* → Select field

4.3. Extract TX3x time series from model at gridbox containing DeBilt station (52.10° N, 5.18° E). Check that the model gridpoint captures the physics of the station location (e.g. land point and not sea point, flat not mountainous etc). → *Get grid points, average area or generate subset*

a. → *Latitude:* “52.1” *°N* - “52.1” *°N*

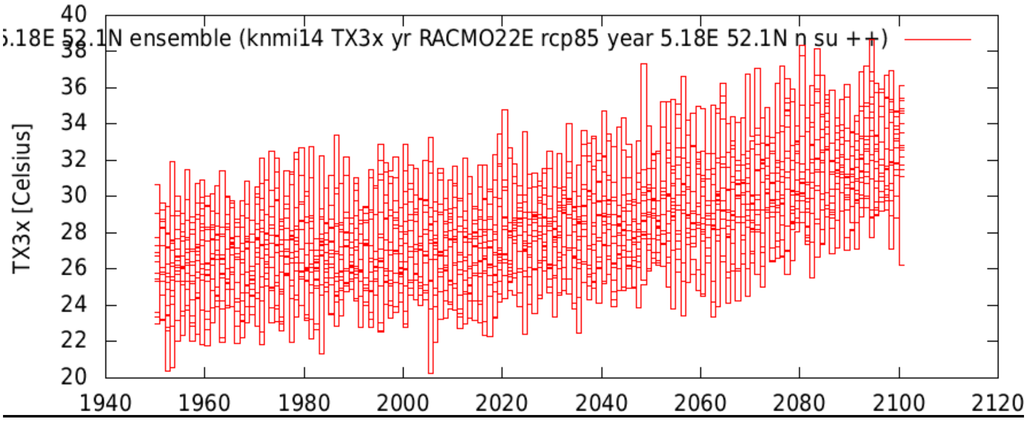
b. → *Longitude:* “5.18” *°E* - “5.18” *°E*

c. → *Make:* **average**

d. → *Considering:* **everything**

e. → *Units:* **convert to Celcius**

f. → Make time series



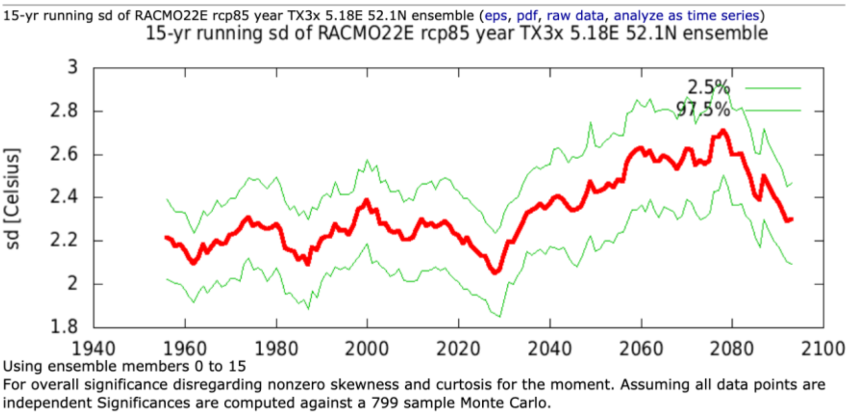
Check variability and seasonal cycle

4.4. RACMO Tmax

4.5. → *Investigate this time series* → Running mean/s.d./skew/curtosis

a. *Running:* **s.d.**

b. Compute



Model GMST

4.6. Since RACMO is downscaled use GMST from from EC-Earth2.3 → *Select a field* → Attribution runs → *The Netherlands* (listed below selection table) → *EC-Earth 2.3 T159* annual mean ensemble mean global temperature

Fitting GEV distribution

4.7. Return to extracted TX3x time series → *Select a time series* → View, upload your time series → RACMO22E rcp85 year TX2x 5.18E 52.1N ensemble (or something similar)

4.8. Go to the attribution tool: → *Investigate this time series* → Trends in return times of extremes

4.9. Select the covariate time series: → *Covariate series* → *User-defined annual timeseries* → **Tglobal EC-Earth23**

4.10. Specify parameters of attribution analysis:

a. *Years:* “” - “2019” [2]
b. *Use:* → **Block maxima** *and fig GEV using* **1** *yr blocks,* → **constrain shape to ±0.4** *of GEV only if no constraint does not work*
c. *Assume: the PDF* **shifts** *with the covariate*, because the analysed event is a temperature event
d. *Return time: year* “2018”. The *choose to include it* box can be ticked in this case (always include the event to avoid a bias)
e. *Compare: return time if it had occurred in year* “1900”
Compare: return time if it had at covariate value “-1.1” (for GMST2018-GMSTpast, -1.2 for GMST2020-GMSTpast)
f. *Bias correction: evaluate for a return period of* “6” *yr*
g. → Compute

Results

4.11. Input the relevant values into the results spreadsheet, and save figures and files like in Step 3.

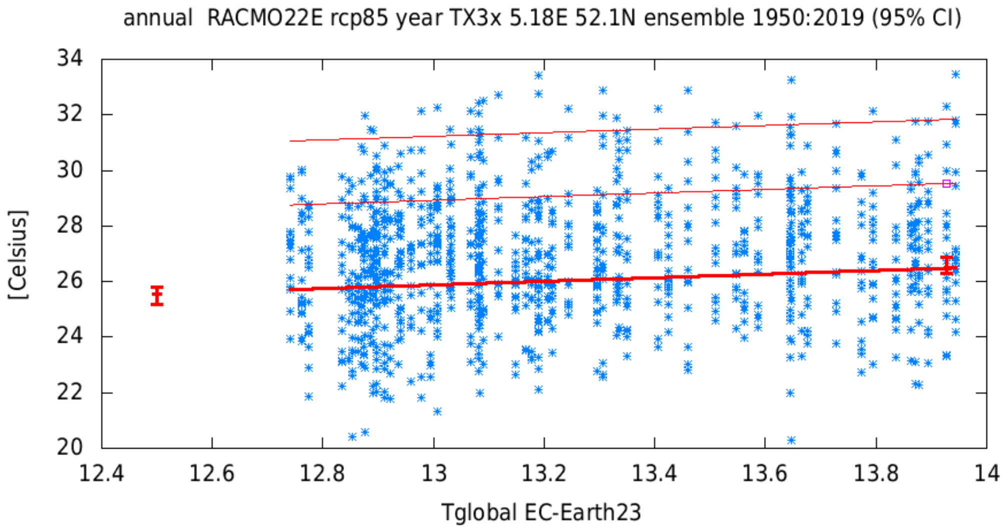
Step 5: Model attribution

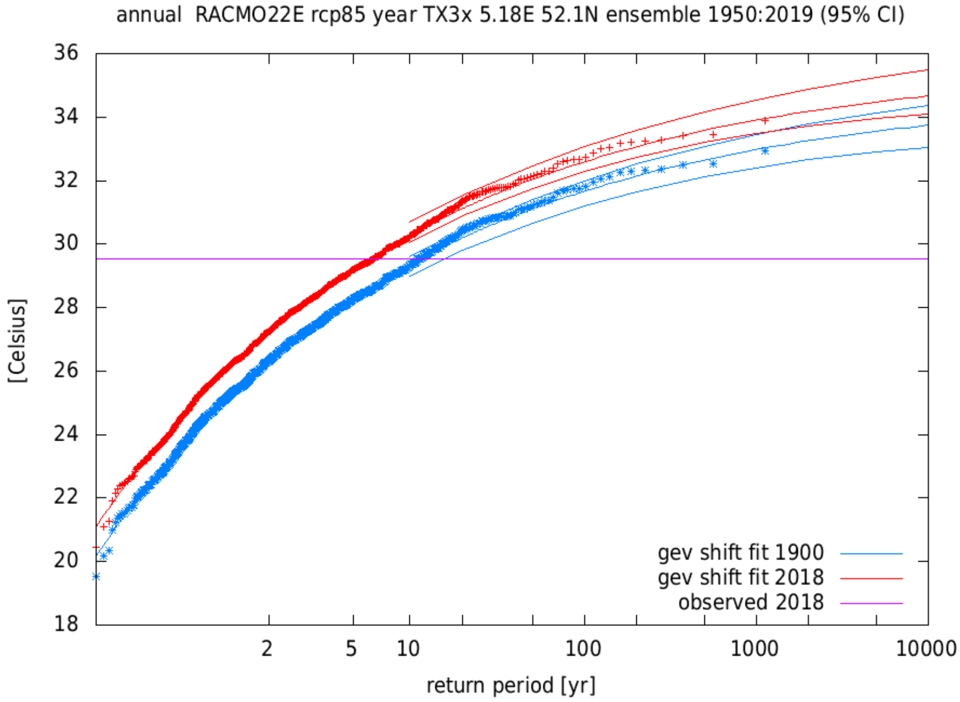
Comparison with past

In this example, the attribution is not different from the validation from the previous step, since model data is only available from 1950 onwards.

annual RACMO22E rcp85 year TX3x 5.18E 52.1N ensemble TX3x [Celsius] dependent on Tglobal EC-Earth23			
parameter	**year**	**value**	**95% CI**
covariate:	1900	12.500	
	2018	13.927	
N:		1120	
Fitted to GEV distribution P(x) = exp(-(1+ξ(x-μ')/σ')^(-1/ξ))			
with μ'= μ+αT and σ' = σ and a Gaussian penalty on ξ of width 0.2			
μ':	1900	25.555	25.422... 25.688
σ':	1900	2.174	2.068... 2.264
μ':	2018	26.480	26.347... 26.614
σ':	2018	2.174	2.068... 2.264
ξ:		-0.235	-0.265... -0.201
α:		0.649	0.384... 1.119
return period event 2018 (value 29.529 at 007)	1900	11.421	9.4824 ... 15.681
probability	1900	0.87559E-01	0.63773E-01 ... 0.10546
return period 2018 (value 29.529 at 007)	2018	6.0000	4.7465 ... 6.9302
probability	2018	0.16667	0.14430 ... 0.21068
probability ratio		1.9035	1.4659 ... 3.0443
p-value probability ratio (one-sided)	≠ 1	0.0010	
change in intensity 1900-2018	diff	0.926	0.548 ... 1.597

[2] No need to add a starting year here, as the model data is available from 1950 onwards, and therefore choosing data up to 2019 automatically corresponds to the period where observational data is available.





Comparison with future

5.1. Same as steps 4.7 - 4.9 above

5.2. Specify parameters of attribution analysis same as 4.10 above, except:

a. Use all years up to 2050: → *Years:* “” - “2050”

b. → *Return time: year* “2050” *with value:* “29.529”

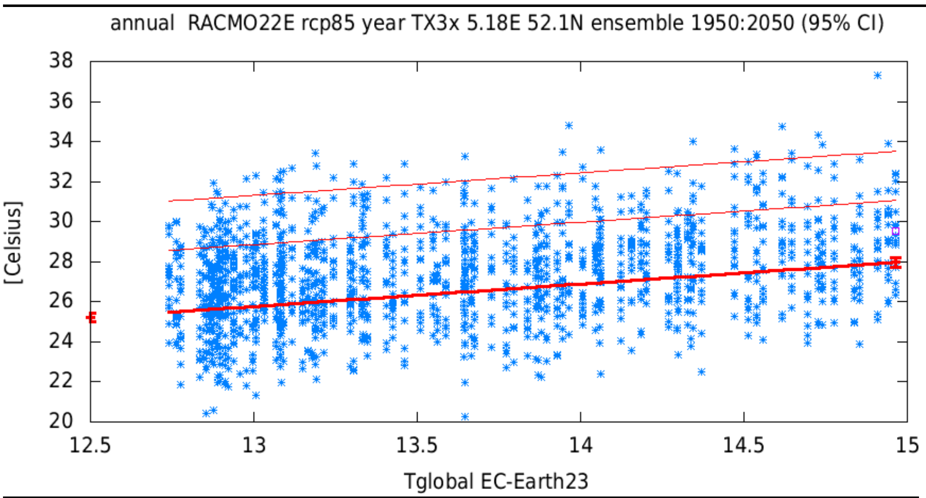
Alternatively: use "2018" with value: “29.529”

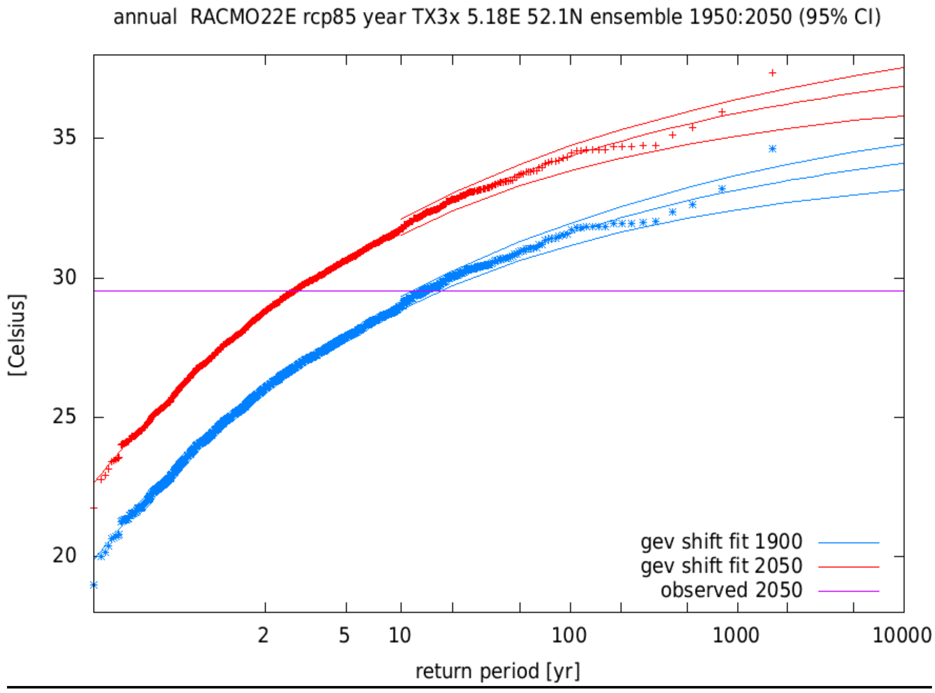
c. → *Compare: return time if it had occurred in year* “1900”

Compare: return time if it had at covariate value “0.8” (for GMSTfuture wrt GMST2020, so use inverse probability ratio)

d. → Compute

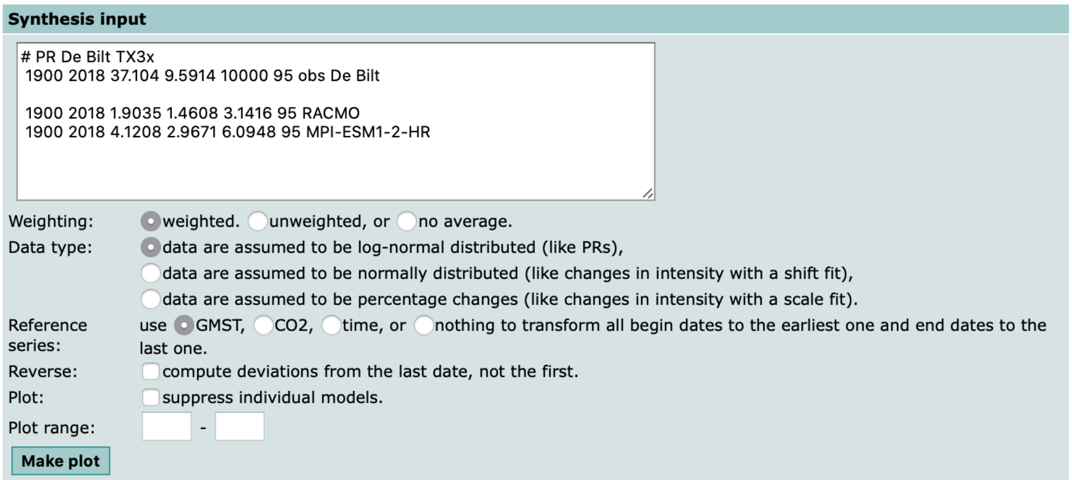
annual RACMO22E rcp85 year TX3x 5.18E 52.1N ensemble TX3x [Celsius] dependent on Tglobal EC-Earth23			
parameter	**year**	**value**	**95% CI**
covariate:	1900	12.500	
	2050	14.965	
N:		1616	
Fitted to GEV distribution P(x) = exp(-(1+ξ(x-μ')/σ')^(-1/ξ))			
with μ'= μ+αT and σ' = σ and a Gaussian penalty on ξ of width 0.2			
μ':	1900	25.208	25.108... 25.332
σ':	1900	2.151	2.070... 2.231
μ':	2050	27.964	27.865... 28.088
σ':	2050	2.151	2.070... 2.231
ξ:		-0.205	-0.246... -0.178
α:		1.118	0.939... 1.279
return period event 2050 (value 29.529)	1900	13.838	11.408 ... 16.811
probability	1900	0.72266E-01	0.59484E-01 ... 0.87660E-01
return period event 2050 (value 29.529)	2050	2.7367	2.4516 ... 3.0836
probability	2050	0.36540	0.32430 ... 0.40790
probability ratio		5.0563	3.8934 ... 6.5721
p-value probability ratio (one-sided)	≠ 1	0.0010	
change in intensity 1900-2050	diff	2.756	2.314 ... 3.153

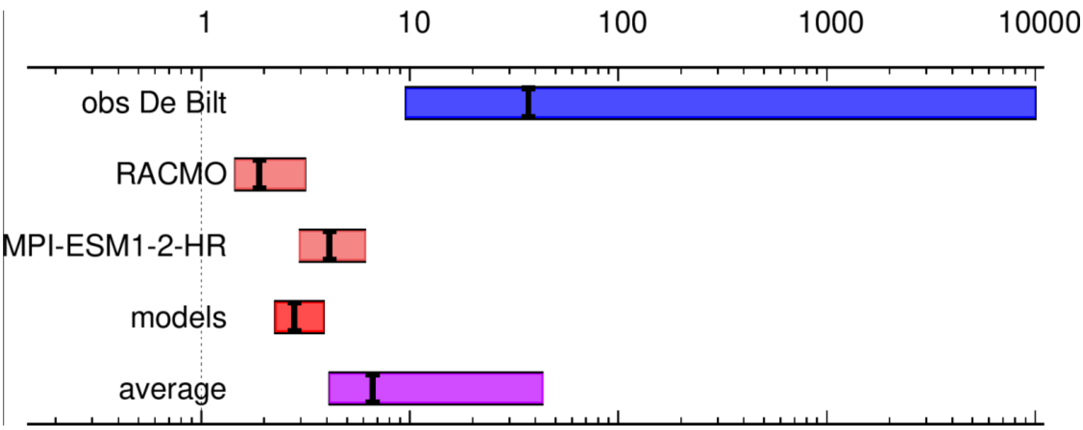




Step 6: Synthesis

See instructions in the Generalised steps section above.





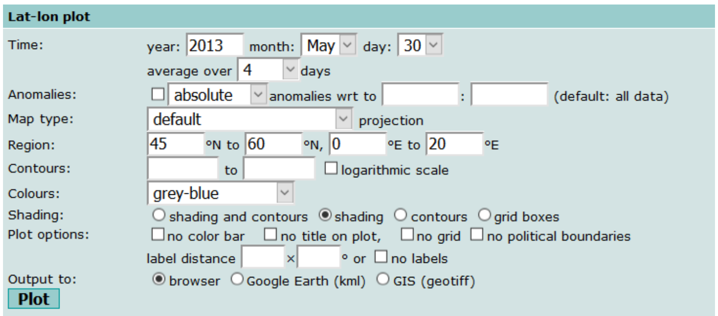
Precipitation example: Extreme rainfall May-June 2013

Extreme rainfall 30 May - 2 June 2013, which resulted in flooding (mainly) of the Elbe and Danube river basins. This example shows only E-Obs and EC-Earth data.

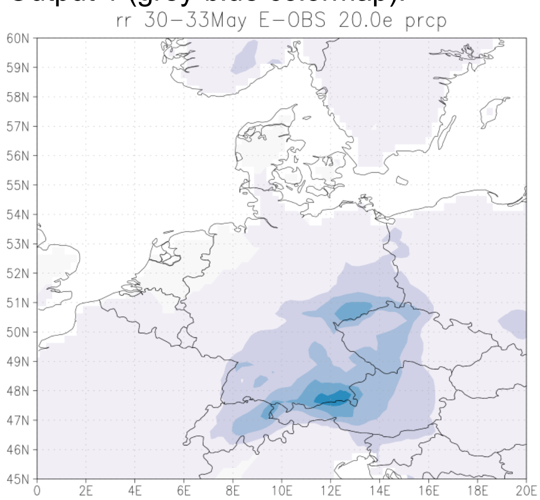
Step 2: Event definition

Create a map of the event

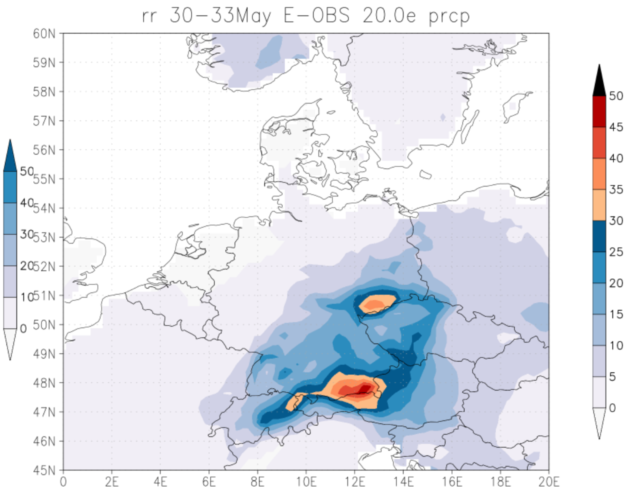
1. Under *Select a field* on the right hand side choose Daily fields
2. Select variable: → *Observations* → *E-OBS 1950-now 0.25° Europe* and *Prcp*
3. Select Plot this field.
4. Under *Lat-lon plot* fill out:
    a. *Time:*
        i. *year:* "2013" *month:* "May" *day:* "30"
        ii. *average over* "4" *days*
    b. *Map type:* **default**
    c. *Region:* "45" *°N to* "60" *°N,* "0" *°E to* "20" *°E*
    d. Select appropriate colormap → *Colours*. Since the variable plotted is precipitation, use a sequential colormap, e.g. **grey-blue**
    e. Use default shading: → **shading**



Output 1 (grey-blue colormap):



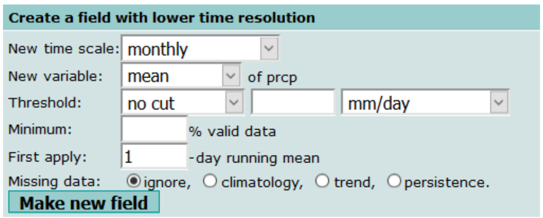
Output 2 (grey-blue-red colormap):



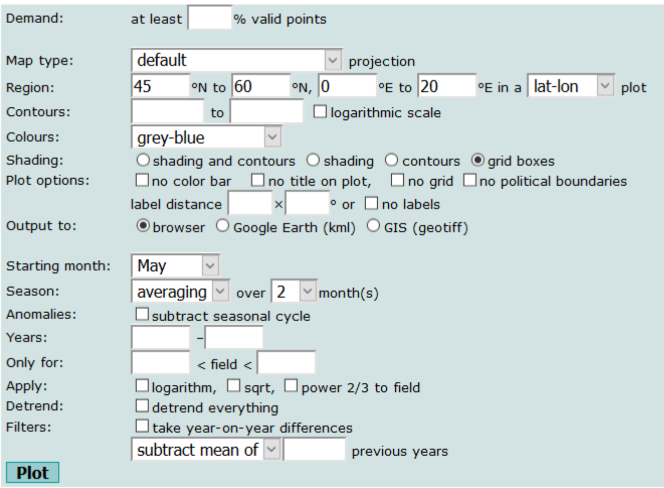
Create a climatology map

Since the analysis was constrained to May-June extreme precipitation events, the climatological map was created for average precipitation for May-June.

5. Under *Select a field* on the right hand side choose Daily fields
6. Select variable: → *Observations* → *E-OBS 1950-now 0.25° Europe* and *Prcp*
7. Make monthly averages: → *Create a field with lower time resolution*
    a. → *New time scale:* **monthly**
    b. → *New variable:* **mean**
    c. Use default settings for *Threshold*, *Minimum* and *Missing data*
    d. Do not apply a running mean: → *First apply:* "1"
    e. Compute monthly averages field: → Make new field. This can take a while.

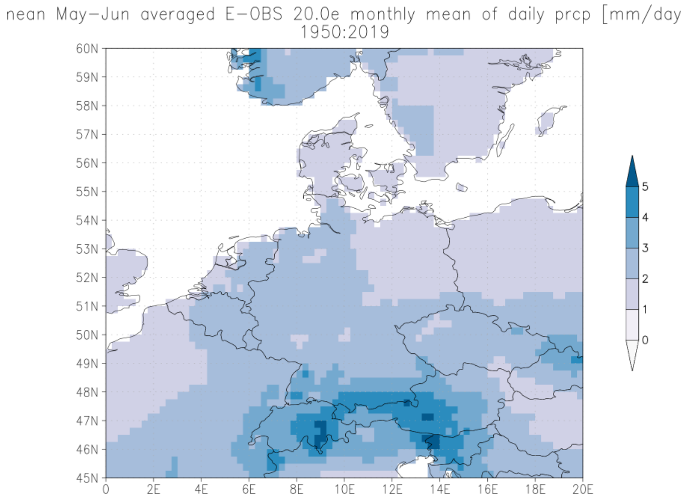


8. Create climatology: → *Investigate this field* → Compute mean, s.d. or extremes
    a. *Property* → **mean,**
    b. *Map type:* **default**
    c. *Region:* "45" *°N* to "60" *°N,* "0" *°E* to "20" *°E in a* **lat-lon** *plot*
    d. Select appropriate colormap → *Colours*. Since the variable plotted is precipitation, use a sequential colormap, e.g. **grey-blue**
    e. Specify the shading: → **grid boxes**
    f. Average of May and June: → *Starting month*: **May**, → *Season:* **averaging** *over* **2** *month(s)*



    g. → Plot

h. The plot parameters can be adjusted after the climatology is generated → *Replot*, e.g. specifying bounds on colorbar → *Contours* “0” *to* “5”



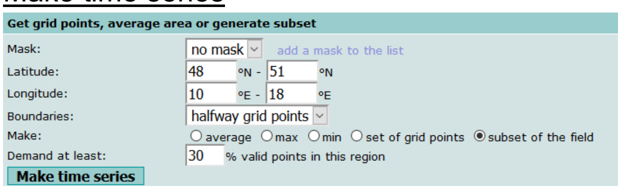
Step 3: Observed probability and trend

Extracting precipitation time series from fields

Upper Elbe basin

A daily precipitation time series was extracted for the upper Elbe basin (Elbe basin south of 51°N), to be used in the observational analysis.

1. Under *Select a field* on the right hand side choose Daily fields
2. Select variable: → *Observations* → *E-OBS 1950-now 0.25° Europe* and *Prcp*
3. Make a subset of E-OBS daily precipitation field which contains the upper Elbe basin south of 51° N: → *Get grid points, average area or generate subset*
    a. *Mask*: **no mask**
    b. *Latitude:* “48” to “51” °N
    c. *Longitude:* “10” to “18” °E
    d. *Make:* → **subset of the field**
    e. Make time series



4. Create a time series of average daily precipitation over the upper Elbe basin: → *Get grid points, average area or generate subset*
    a. → add a mask to the list

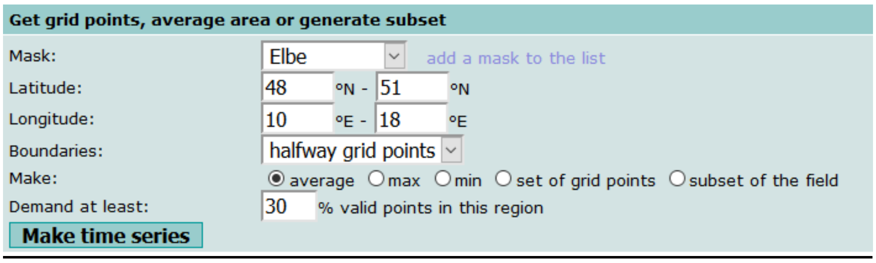
b. click on ‘paper’-icon  to the right of *14 European river catchments* → right-click on *Elbe catchment* to save the lat-lon mask in a .txt file for comms.

c. Return to page from step *a* by clicking the back button in your browser → 14 European river catchments

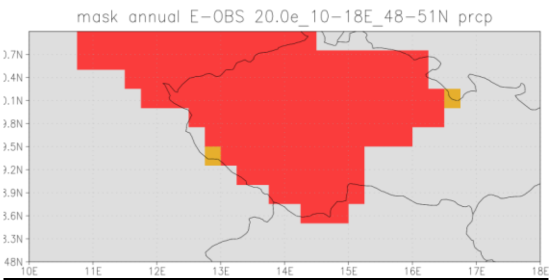
d. From the *Mask* dropdown menu select **Elbe**

e. *Make:* → **average**

f. Make time series

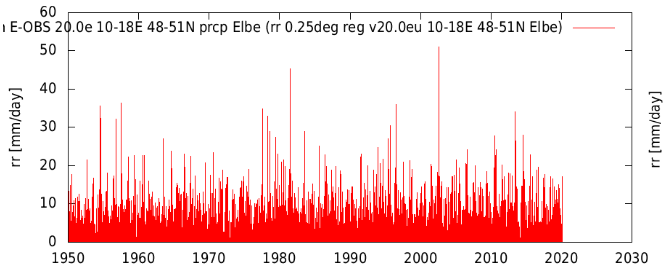


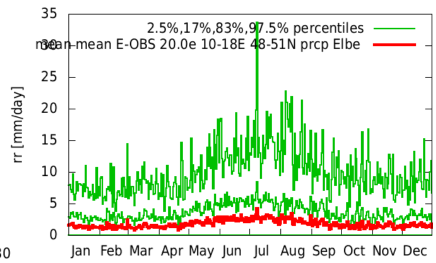
5. Save the mask file: → *Download* mask file



6. The daily precipitation time series is saved by the CE → View, upload your time series → *Daily time series* → E-OBS 20.0e 10-18E 48-51N prcp Elbe

7. Save or copy figures of time series and annual Jan-Dec cycle by right clicking on them.





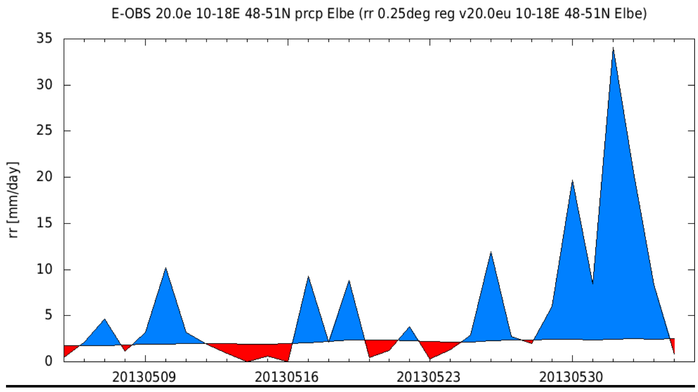
8. Plot the last 30 days before and including the event: → *Investigate this time series* → *View last* 30 *days*

a. → *Replot:* “30” *days with end date* “2013” - “06” - “03”

b. → *Plot:* **observations**

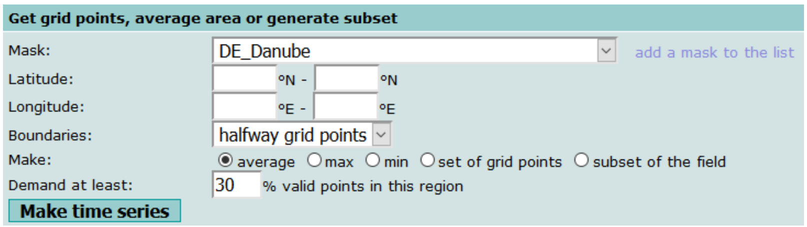
c. *Compare with:* **climatology** “1981” - “2010”

d. → plot



Upper Danube basin

9. Under *Select a field* on the right hand side choose Daily fields
10. Select variable: → *Observations* → *E-OBS 1950-now 0.25° Europe* and *Prcp*
11. Create a time series of average daily precipitation over the upper Elbe basin: → *Get grid points, average area or generate subset*
    a. → add a mask to the list
    b. click on 'paper'-icon to the right of *215 European river basins* → right-click on *RBD_F1v3.0 river basin DE Danube (de: Donau)* to save the lat-lon mask in a .txt file for comms.
    c. Return to page from step *a* by clicking the back button in your browser → 215 European river basins
    d. *Mask:* **DE_Danube**
    e. *Make:* → **average**
    f. Make time series

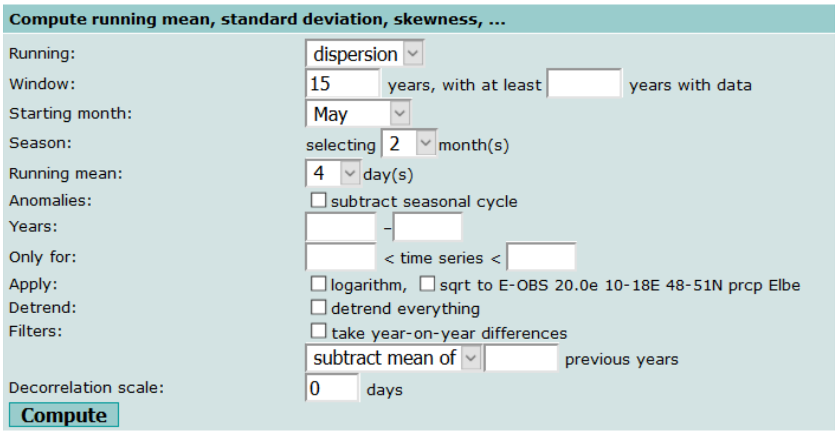


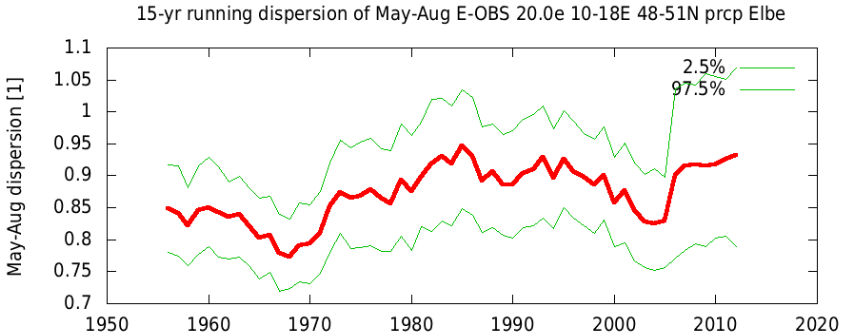
12. The daily precipitation time series is saved by the CE → View, upload your time series → *Daily time series* → E-OBS 20.0e prcp DE Danube
13. Repeat step 7 and 8 from the upper Elbe basin example.

Variability check

14. Select the daily precipitation time series already saved by the CE → View, upload your time series → *Daily time series* → E-OBS 20.0e 10-18E 48-51N prcp Elbe
15. For precipitation the attribution procedure assumes that dispersion (standard deviation/mean) is constant. Therefore the temporal variability of the timeseries is checked: → *Investigate this time series* → Running mean/s.d./skew/curtosis

a. *Running:* **dispersion**
b. *Starting month:* **May**
c. *Season: selecting* **2** *month(s)*
d. *Running mean:* **4** *day(s)*
e. → Compute





Dispersion does not vary with time more than within uncertainty, so the assumption is fine.

Fitting GEV distribution

This example uses the daily precipitation time series from the upper Elbe basin (only data up to 2013), but the steps for the upper Danube basin are identical.

16. Select the daily precipitation time series already saved by the CE → View, upload your time series → *Daily time series* → E-OBS 20.0e 10-18E 48-51N prcp Elbe
17. Go to the attribution tool: → *Investigate this time series* → Trends in return times of extremes
18. Select the covariate time series: → *Covariate series* → *System-defined annual timeseries* → **smoothed GMST**
19. Specify parameters to generate precipitation extreme time series:
    a. *Starting month:* **May**
    b. *Season: selecting* **2** *month(s)*
    c. *Running mean:* **4** *day(s)*
    d. *Years:* “” - “2013”

e. *Use:* → **Block maxima** *and fig GEV using* **1** *yr blocks,* → **constrain shape to ±0.4** *of GEV only if no constraint does not work*

20. Specify parameters of attribution analysis:
    a. *Assume: the PDF* **scales** *with the covariate*, because the analysed event is a precipitation event.
    b. *Return time: year* "2013". The *choose to include it* box should NOT be ticked (always include the event to avoid a bias)
    c. *Compare: return time if it had occurred in year* "1900"
    Compare: return time if it had at covariate value "-1.0" (for GMST2013-GMSTpast, about 1.2 for GMST2020-GMSTpast)
    d. → Compute

Plot	
Starting month:	May
Season:	selecting 2 month(s)
Running mean:	4 day(s)
Anomalies:	☐ subtract seasonal cycle
Years:	-2013
Apply:	☐ logarithm, ☐ sqrt, ☐ square , ☐ cube , ☐ power 2/3 to series E-OBS 20.0e 10-18E 48-51N prcp Elbe
Detrend:	☐ detrend everything
Demand at least	% valid points
Change sign:	☐ study the low extremes
Use:	○ Average and fit normal distribution ○ Block maxima and fit Gumbel distribution ◉ Block maxima and fit GEV using 1 -yr blocks ○ Peak over threshold 80 % and fit GPD constrain shape to ±0.4 of GEV and GPD
Assume:	the PDF ○ shifts, ◉ scales or ○ both with the covariate
Return time:	year 2013 (with value), this year is excluded from the fit unless the value is specified or you ☐ choose to include it
Compare:	return time if it had occurred in year 1900
Optionally plot:	return time if it had occurred in year
Bias correction:	evaluate for a return period of yr or add % and/or mm/day.
Plot range:	X : , Y :
Confidence interval:	95 % ☐ use amoeba
Compute	

Results

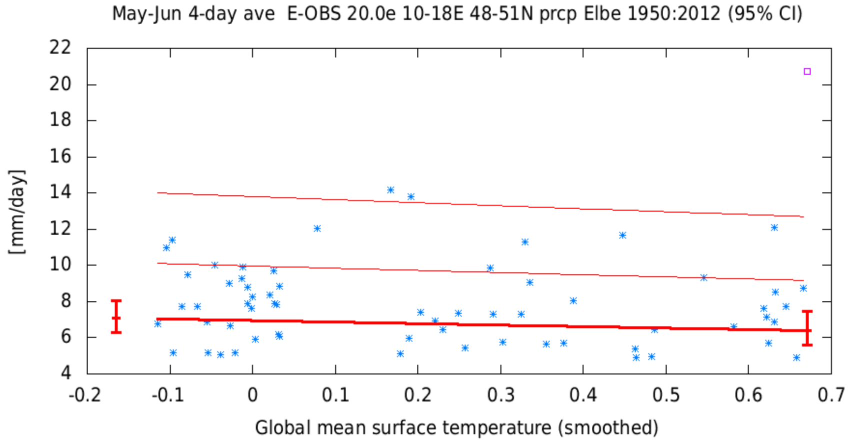
21. Save or copy a screenshot of the results table:

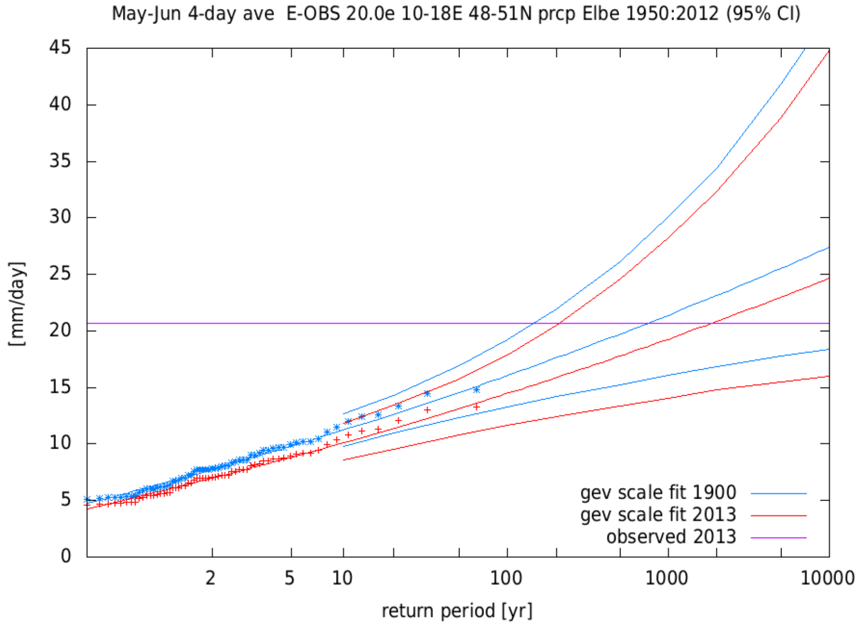
May-Jun 4-day ave E-OBS 20.0e 10-18E 48-51N prcp Elbe rr [mm/day] dependent on Global mean surface temperature (smoothed)			
parameter	**year**	**value**	**95% CI**
covariate:	1900	-0.16542	
	2013	0.67125	
N:		63	
Fitted to GEV distribution P(x) = exp(-(1+ξ(x-μ')/σ')^(-1/ξ))			
with μ' = μ exp(αT/μ) and σ' = σ exp(αT/μ) and a Gaussian penalty on ξ of width 0.2			
μ':	1900	7.101	6.622... 7.648
σ':	1900	1.730	1.382... 2.011
μ':	2013	6.398	5.919... 6.945
σ':	2013	1.559	1.235... 1.826
σ/μ:		0.244	0.201... 0.272
ξ:		0.051	-0.082... 0.207
α:		-0.844	-2.654... 0.952
return period event 2013 (value 20.699)	1900	747.65	146.42 ... 0.15430E+06
probability	1900	0.13375E-02	0.64811E-05 ... 0.68295E-02
return period event 2013 (value 20.699)	2013	1872.6	208.74 ... 0.16138E+08
probability	2013	0.53402E-03	0.61965E-07 ... 0.47906E-02
probability ratio		0.39926	0.16892E-02 ... 3.9845
inverse probability ratio		2.5046	0.25097 ... 591.98
p-value probability ratio (one-sided)	≠ 1	0.1877	
change in intensity 1900-2013	diff %	-9.900	-27.838 ... 12.255

22. Copy and paste values into results spreadsheet:
    a. Ynow: *2013*

b. Ypast: *1900*
Compare: return time if it had at covariate value “-1.0” (for GMST2013-GMSTpast, -1.2 for GMST2020-GMSTpast)
c. Dispersion σ/μ: *0.224 (0.201 … 0.272)*
d. Shape ξ: *-0.227 (-0.315 … -0.133)*
e. The 2013 event magnitude: *20.699* mm/day
f. Return period of 2013 event: *1872.6 (208.74 ... 0.16138E+08)* yr
g. Probability ratio: *0.39926 (0.16892E-02 ... 3.9845)*
h. Change in intensity: *-9.900 (-27.838 ... 12.255)* %diff

23. Save or copy figures. If figures are to be used later save as eps file.





24. Save the values the figures are based by right clicking on raw data, and saving it as a .txt file. This is useful if you want to store the data or make your own figures. Additionally, the results table is contained in the text file attached to the event variable vs. return period plot (in HTML-format).

Step 4: Model validation

This example shows how to do the model validation for EC-EARTH, which is available in the CE.
If the model data is not available in the CE, it is also possible to upload the daily precipitation time series into the CE. If you are using the second option proceed directly to Check

variability and seasonal cycle. However, do not forget to check the spatial pattern by generating a climatology field. This can also be uploaded and plotted by the climate explorer.

Spatial pattern

4.1. Select the EC-EARTH precipitation data for the RCP8.5 scenario: → *Select a field* → Attribution runs → *EC-Earth 2.3 T159 coupled 1860-2100* → *16 monthly* → *RCP8.5* → *pr*

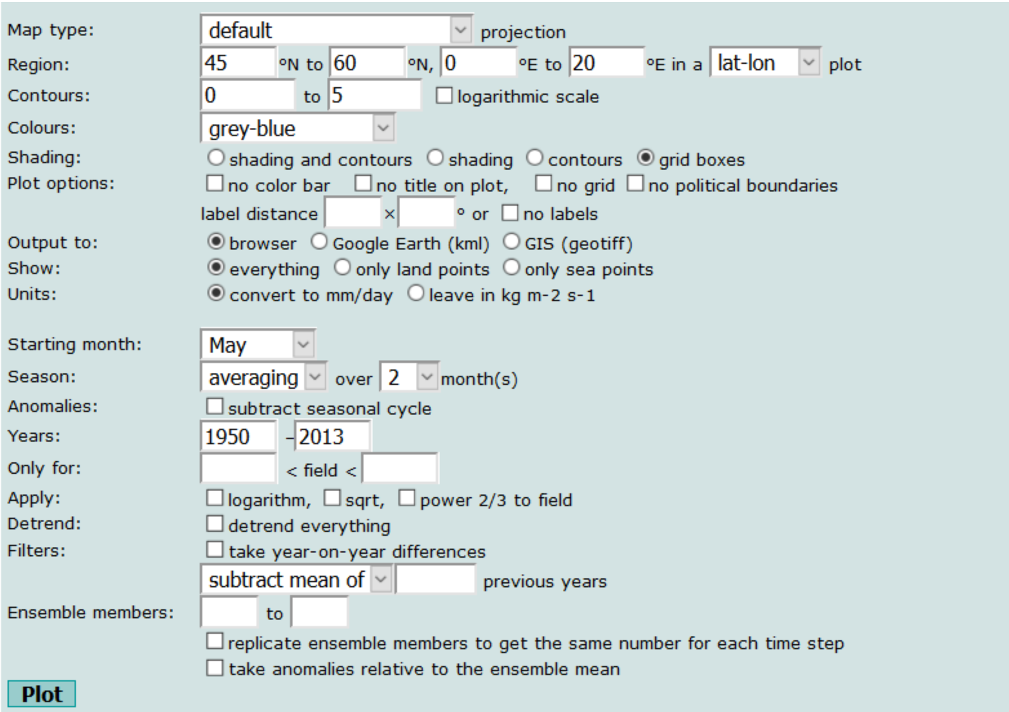
4.2. → Select field

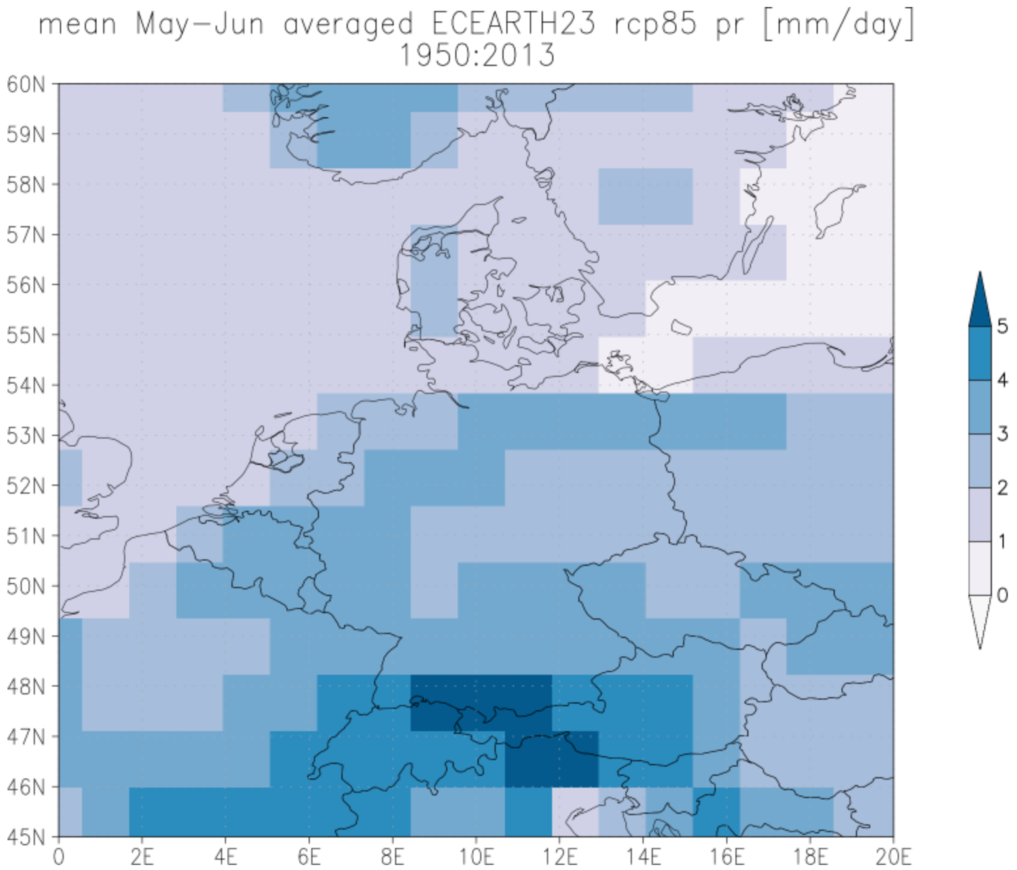
4.3. → *Investigate this field* → Compute mean, s.d. or extremes

4.4. Follow instructions in from Step 4 in the Create a climatology map section above.

a. However, only use the years 1950-2013: → *Years*

b. And convert the units: → *Units* → **convert to mm/day**





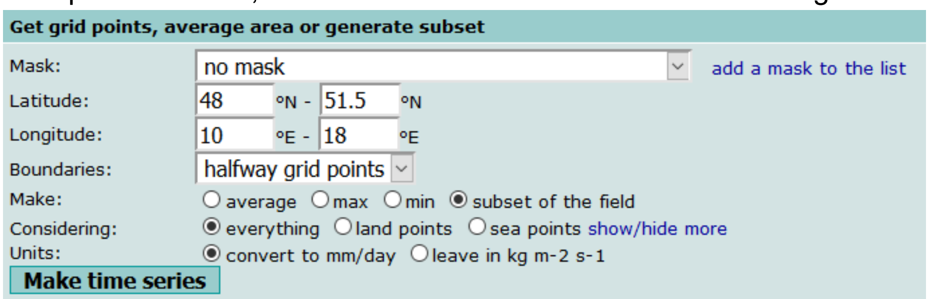
Extracting precipitation time series from EC-EARTH

4.5. Select the EC-EARTH precipitation data for the RCP8.5 scenario: → *Select a field* → Attribution runs → *EC-Earth 2.3 T159 coupled 1860-2100* → *16 daily* → *RCP8.5* → *pr*

4.6. → Select field

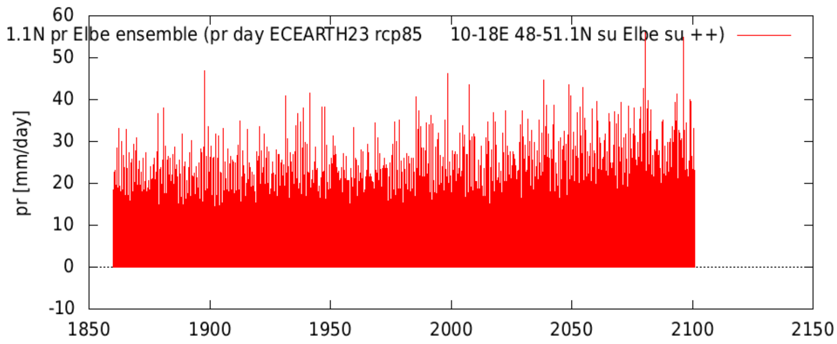
4.7. Follow steps from Step 3 described above for the Elbe and the Danube.

a. Except for the Elbe, use the data south of 51.5°N when creating a subset.



b. Note that extracting data from modelled datasets take much longer due to the ensemble members.

4.8. Save or copy figure of time series by right clicking on them.

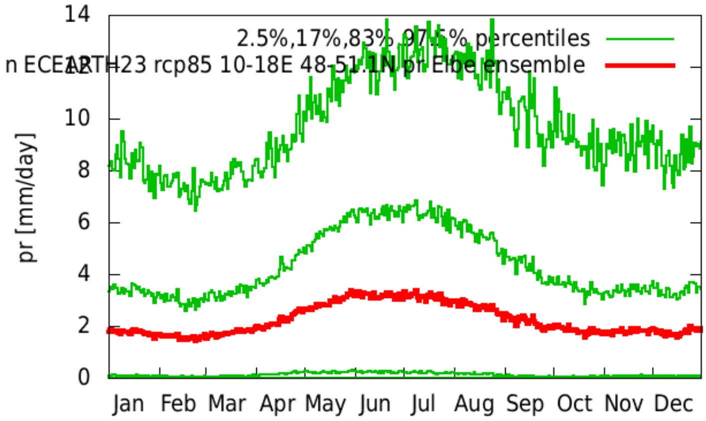


Check seasonal cycle and variability

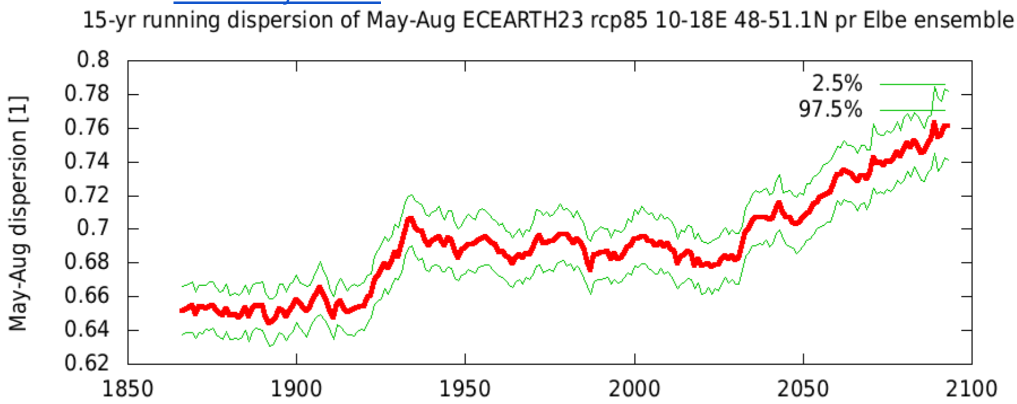
4.9. Check the modelled seasonal cycle against the observed one.

a. → *Manipulate this time series* → *Select years:* “1950”-”2013” → Select

b. Save seasonal cycle plot, and compare with observed.



4.10. Do a variability check like for the observational data



Model GMST

4.11. Select the EC-EARTH precipitation data for the RCP8.5 scenario: → *Select a field* → Attribution runs → under *The Netherlands* at the bottom of the page → *EC-Earth 2.3 T159* → annual mean ensemble mean global mean temperature

Fitting GEV distribution

4.12. Select the daily precipitation time series you extracted from the model → *Select a time series* → View, upload your time series

4.13. Go to the attribution tool: → *Investigate this time series* → Trends in return times of extremes

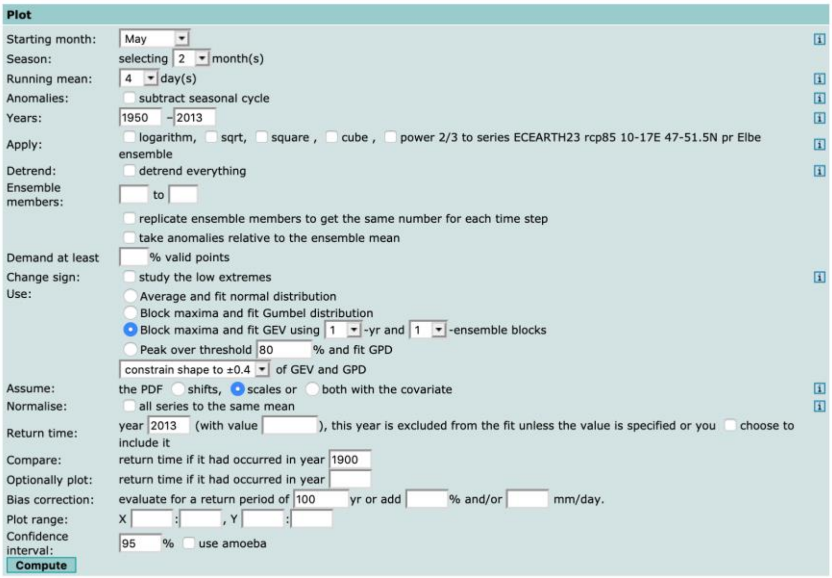
4.14. Select the covariate time series: → *Covariate series* → *User-defined annual timeseries* → **Tglobal EC-Earth23**

4.15. Specify parameters to generate precipitation extreme time series. Same as in the observation analysis, except:

   a. Select only the years where observational data is available → *Years:* “1950” - “2013”

4.16. Specify parameters of attribution analysis. Same as in the observation analysis, except:

   a. *Bias correction:evaluate for a return period of* “100” *yr*



Results

May-Jun 4-day ave ECEARTH23 rcp85 10-18E 48-51.1N pr Elbe ensemble pr [mm/day] dependent on Tglobal EC-Earth23			
parameter	**year**	**value**	**95% CI**
covariate:	1900	12.500	
	2013	13.836	
N:		1024	
Fitted to GEV distribution P(x) = exp(-(1+ξ(x-μ')/σ')^(-1/ξ))			
with μ' = μ exp(αT/μ) and σ' = σ exp(αT/μ) and a Gaussian penalty on ξ of width 0.2			
μ':	1900	6.857	6.746... 6.979
σ':	1900	1.647	1.559... 1.725
μ':	2013	7.713	7.601... 7.835
σ':	2013	1.853	1.757... 1.936
σ/μ:		0.240	0.229... 0.251
ξ:		0.005	-0.034... 0.042
α:		0.640	0.258... 1.055
return period event 2013 (value 16.343 at 004)	1900	290.65	160.94 ... 693.79
probability	1900	0.34406E-02	0.14414E-02 ... 0.62136E-02
return period 2013 (value 16.343 at 004)	2013	100.00	62.992 ... 176.29
probability	2013	0.10000E-01	0.56725E-02 ... 0.15875E-01
probability ratio		2.9065	1.5139 ... 6.2186
p-value probability ratio (one-sided)	≠ 1	0.0024	
return value 100 yr	1900	14.530	13.699 ... 15.385
	2013	16.343	15.413 ... 17.371
change in intensity 1900-2013	diff %	12.475	4.864 ... 21.339

4.17. Save or copy a screenshot of the results table and figures, and add it to the Notes document.

4.18. Copy and paste the fit parameter values into results spreadsheet, together with information on seasonal cycle and spatial pattern.

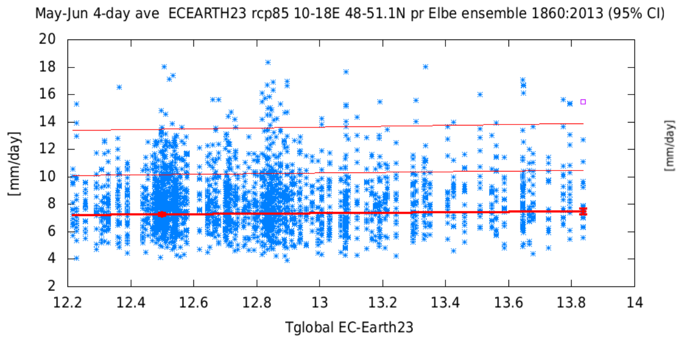
Step 5: Model attribution

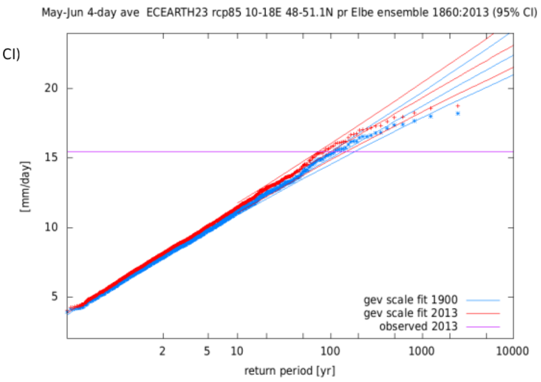
Comparison with past

5.1. Exactly like in model validation above, except use all the years up to event:

a. → *Years:* “1950” - “2013”

May-Jun 4-day ave ECEARTH23 rcp85 10-18E 48-51.1N pr Elbe ensemble pr [mm/day] dependent on Tglobal EC-Earth23			
parameter	**year**	**value**	**95% CI**
covariate:	1900	12.500	
	2013	13.836	
N:		2464	
Fitted to GEV distribution P(x) = exp(-(1+ξ(x-μ')/σ')^(-1/ξ))			
with μ' = μ exp(αT/μ) and σ' = σ exp(αT/μ) and a Gaussian penalty on ξ of width 0.2			
μ':	1900	7.273	7.191... 7.348
σ':	1900	1.714	1.657... 1.765
μ':	2013	7.500	7.418... 7.574
σ':	2013	1.767	1.709... 1.819
σ/μ:		0.236	0.228... 0.242
ξ:		-0.009	-0.033... 0.016
α:		0.169	-0.028... 0.354
return period event 2013 (value 15.470 at 004)	1900	132.74	99.403 ... 182.86
probability	1900	0.75334E-02	0.54688E-02 ... 0.10060E-01
return period 2013 (value 15.470 at 004)	2013	100.00	73.316 ... 146.46
probability	2013	0.10000E-01	0.68279E-02 ... 0.13640E-01
probability ratio		1.3274	0.95205 ... 1.8313
p-value probability ratio (one-sided)	≠ 1	0.0498	
return value 100 yr	1900	15.002	14.568 ... 15.481
	2013	15.470	14.881 ... 16.055
change in intensity 1900-2013	diff %	3.120	-0.514 ... 6.671





5.2. Save or copy a screenshot of the results table and figures, and add it to the Notes document.

5.3. Copy and paste the probability ratio and change in intensity values into results spreadsheet

Comparison with future

5.4. Just like above, except:

a. Use all years up to 2050: → *Years:* “” - “2050”

b. → *Return time: year* “2050” *with value:* “15.470”

Alternatively: use "2013" with value: "15.470"

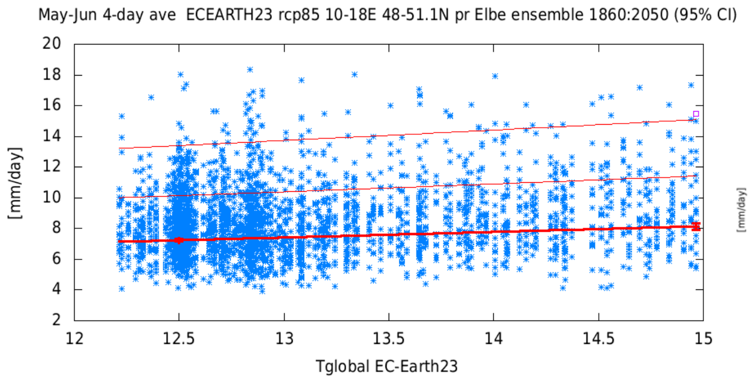
c. → *Compare: return time if it had occurred in year* “1900”

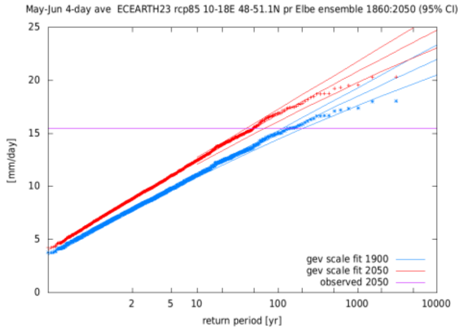
Compare: return time if it had at covariate value “0.8” (for GMSTfuture wrt GMST2020, so use inverse probability ratio)

d. No bias correction

e. → Compute

May-Jun 4-day ave ECEARTH23 rcp85 10-18E 48-51.1N pr Elbe ensemble pr [mm/day] dependent on Tglobal EC-Earth23			
parameter	**year**	**value**	**95% CI**
covariate:	1900	12.500	
	2050	14.965	
N:		3056	
Fitted to GEV distribution P(x) = exp(-(1+ξ(x-μ')/σ')^(-1/ξ))			
with μ' = μ exp(αT/μ) and σ' = σ exp(αT/μ) and a Gaussian penalty on ξ of width 0.2			
μ':	1900	7.241	7.165... 7.306
σ':	1900	1.733	1.680... 1.776
μ':	2050	8.150	8.074... 8.215
σ':	2050	1.951	1.893... 1.997
σ/μ:		0.239	0.233... 0.245
ξ:		-0.018	-0.041... 0.003
α:		0.358	0.263... 0.451
return period event 2050 (value 15.470)	1900	142.88	112.57 ... 205.60
probability	1900	0.69988E-02	0.48639E-02 ... 0.88831E-02
return period event 2050 (value 15.470)	2050	49.044	39.334 ... 66.804
probability	2050	0.20390E-01	0.14969E-01 ... 0.25423E-01
probability ratio		2.9134	2.1851 ... 3.9470
p-value probability ratio (one-sided)	≠ 1	0.0010	
change in intensity 1900-2050	diff %	12.553	9.103 ... 16.015



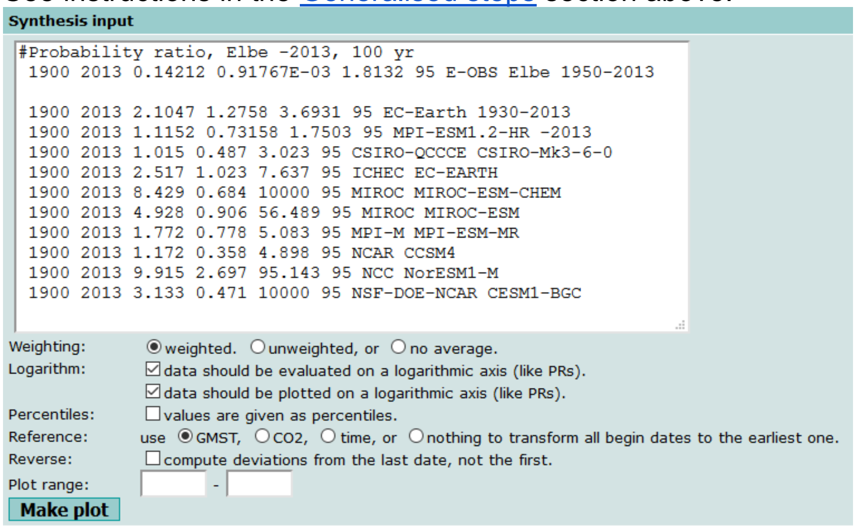


5.5. Save or copy a screenshot of the results table and figures, and add it to the Notes document.

5.6. Copy and paste the probability ratio and change in intensity values into results spreadsheet

Step 6: Synthesis

See instructions in the Generalised steps section above.



Synthesis input

```
#Probability ratio, Elbe -2013, 100 yr
 1900 2013 0.14212 0.91767E-03 1.8132 95 E-OBS Elbe 1950-2013

 1900 2013 2.1047 1.2758 3.6931 95 EC-Earth 1930-2013
 1900 2013 1.1152 0.73158 1.7503 95 MPI-ESM1.2-HR -2013
 1900 2013 1.015 0.487 3.023 95 CSIRO-QCCCE CSIRO-Mk3-6-0
 1900 2013 2.517 1.023 7.637 95 ICHEC EC-EARTH
 1900 2013 8.429 0.684 10000 95 MIROC MIROC-ESM-CHEM
 1900 2013 4.928 0.906 56.489 95 MIROC MIROC-ESM
 1900 2013 1.772 0.778 5.083 95 MPI-M MPI-ESM-MR
 1900 2013 1.172 0.358 4.898 95 NCAR CCSM4
 1900 2013 9.915 2.697 95.143 95 NCC NorESM1-M
 1900 2013 3.133 0.471 10000 95 NSF-DOE-NCAR CESM1-BGC
```

Weighting: (•) weighted. ( ) unweighted, or ( ) no average.
Logarithm: [x] data should be evaluated on a logarithmic axis (like PRs).
[x] data should be plotted on a logarithmic axis (like PRs).
Percentiles: [ ] values are given as percentiles.
Reference: use (•) GMST, ( ) CO2, ( ) time, or ( ) nothing to transform all begin dates to the earliest one.
Reverse: [ ] compute deviations from the last date, not the first.
Plot range: ___ - ___
Make plot

References

Otto, F. E. L., Barnes, C., Philip, S., Kew, S., van Oldenborgh, G. J., and Vautard, R.: Formally combining different lines of evidence in extreme-event attribution, Adv. Stat. Clim. Meteorol. Oceanogr., 10, 159–171, https://doi.org/10.5194/ascmo-10-159-2024, 2024.

Philip, S., Kew, S., van Oldenborgh, G. J., Otto, F., Vautard, R., van der Wiel, K., King, A., Lott, F., Arrighi, J., Singh, R., and van Aalst, M.: A protocol for probabilistic extreme event attribution analyses, Adv. Stat. Clim. Meteorol. Oceanogr., 6, 177–203, https://doi.org/10.5194/ascmo-6-177-2020, 2020.

van Oldenborgh, G.J., van der Wiel, K., Kew, S. *et al.* Pathways and pitfalls in extreme event attribution. *Climatic Change* **166**, 13 (2021). https://doi.org/10.1007/s10584-021-03071-7

Appendix

List of bugs/things to watch out for

- Uploading your own time series
  - For daily time series precipitation units must be expressed in “mm/day”
  - When uploading a time series you MUST choose the **something else** option, under *Type*, or else the CE does not upload your time series (or at least you can’t find it again later under View, upload your time series).
  - OR, scroll down and manually click at Make index “add to list”

Suggestions

- In the attribution tool, separate the actual attribution tool from the generation of the extreme time series (e.g. annual maxima, x-day averaging etc.), so that it is clear that two different things are being done. Or at least make clear which parameters and options pertain to the attribution and which to the extreme time series generation. E.g. the parameters of generating the extreme time series are shown under *Plot* which is misleading. Everything from *Use:* is the actual attribution analysis