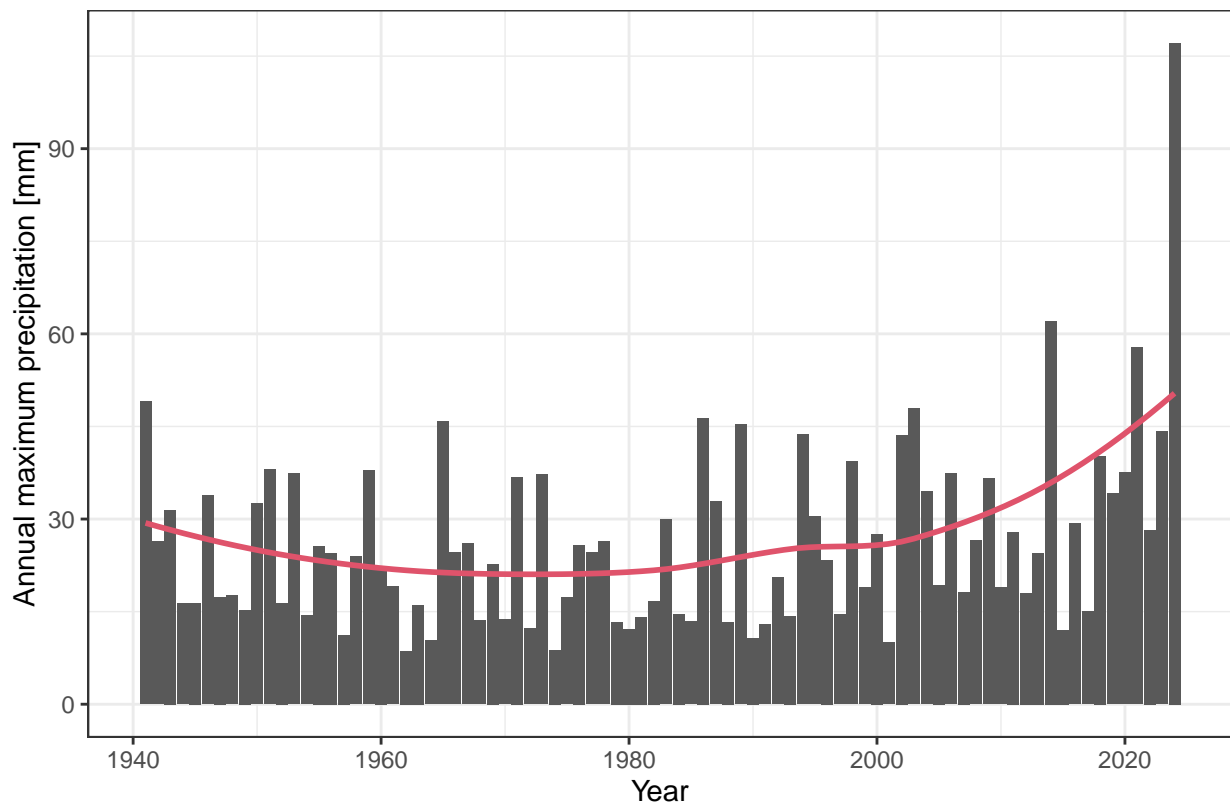


Investigating possible trends in extreme 2-hour precipitation time series - Vienna Hohe Warte

Klaus, Laimighofer, Lehner

2025-07-21

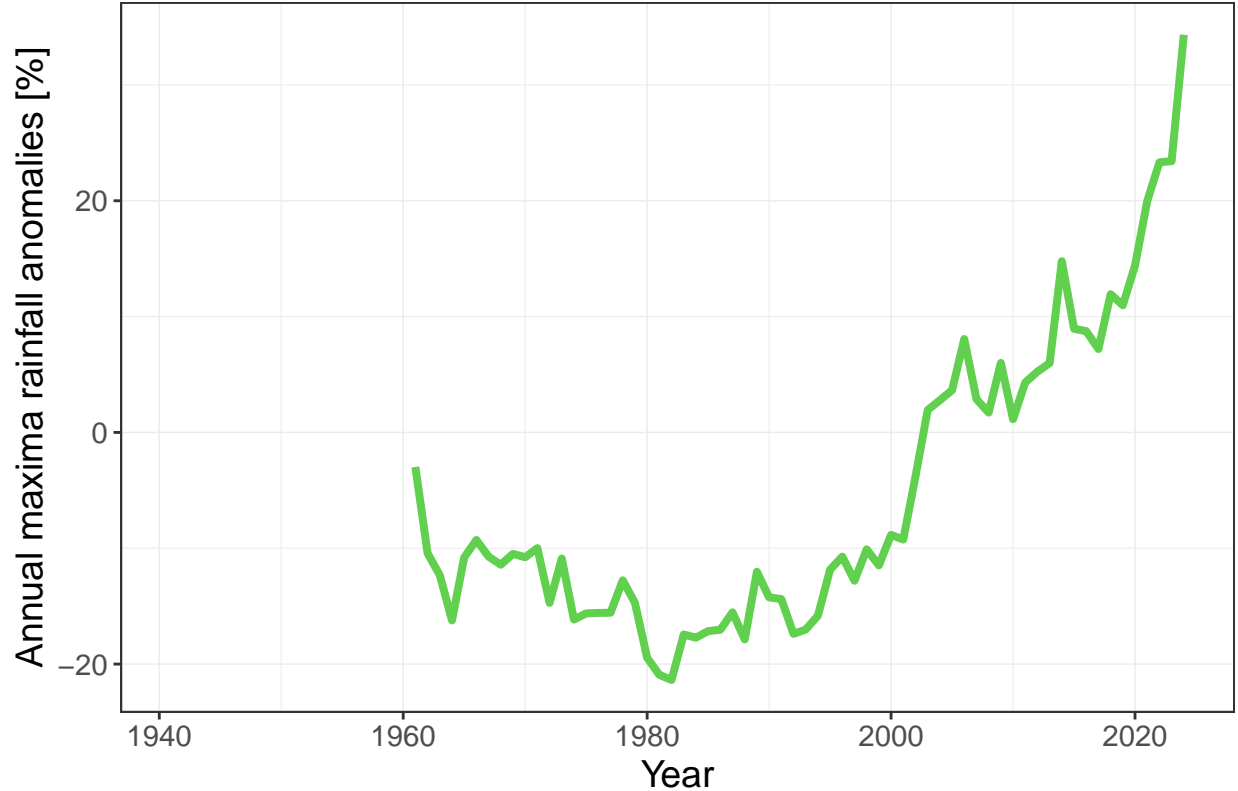
This is an extension to our reviewer reply to the manuscript Klaus, Laimighofer, and Lehner (2025). This short comment focuses on the issue, if our underlying time series does have a trend or not. The data used is based on an hourly time series of precipitation data for Vienna Hohe-Warte ranging from 1941 to 2024. Additionally cloud temperature data is used, computed from ERA5 (Hersbach et al. (2020)) data from 1941 to 2024. Cloud temperature is estimated by the difference of geopotential between 500 hpa and 700 hpa. All processed data can be found under Lehner, Laimighofer, and Klaus (2024). We stated in the first draft of the manuscript that our underlying timeseries of annual maximum precipitation has no trend and therefore a stationary distributional model can be fitted. This statement was tested by a bootstrapped Mann-Kendall trend test, which gave no indication of a trend yielding a p-value of 0.09. A visualization of the time series shows the exceptional event of August 2024. This event was not included in the trend test, as it was also not included in the distributional model. If this event was added to the time series, this would result in a p-value slightly below 0.05: 0.047. In the following comment, we would like to point out that the non-detected trend in the time series can be traced back to several issues.



Annual maxima time series of 2-hour precipitation for Vienna Hohe-Warte

Signal to noise ratio

First, we want to clarify that the high variability in the annual maxima time series is overlaying the signal of the time series, leading to a non-significant trend test. For example Haslinger et al. (2025) showed that hourly precipitation anomalies are on average increasing since the 1960s in Austria. Their approach was to use a rolling window of 21 years of a 0.99 quantile of wet days to smooth the variability in the precipitation time series. Adopting this approach to our annual maxima time series of 2-hour precipitation, we can show an increase in the anomalies for the last 40 years, which exceeds 20 % for the last two years (2023 and 2024).



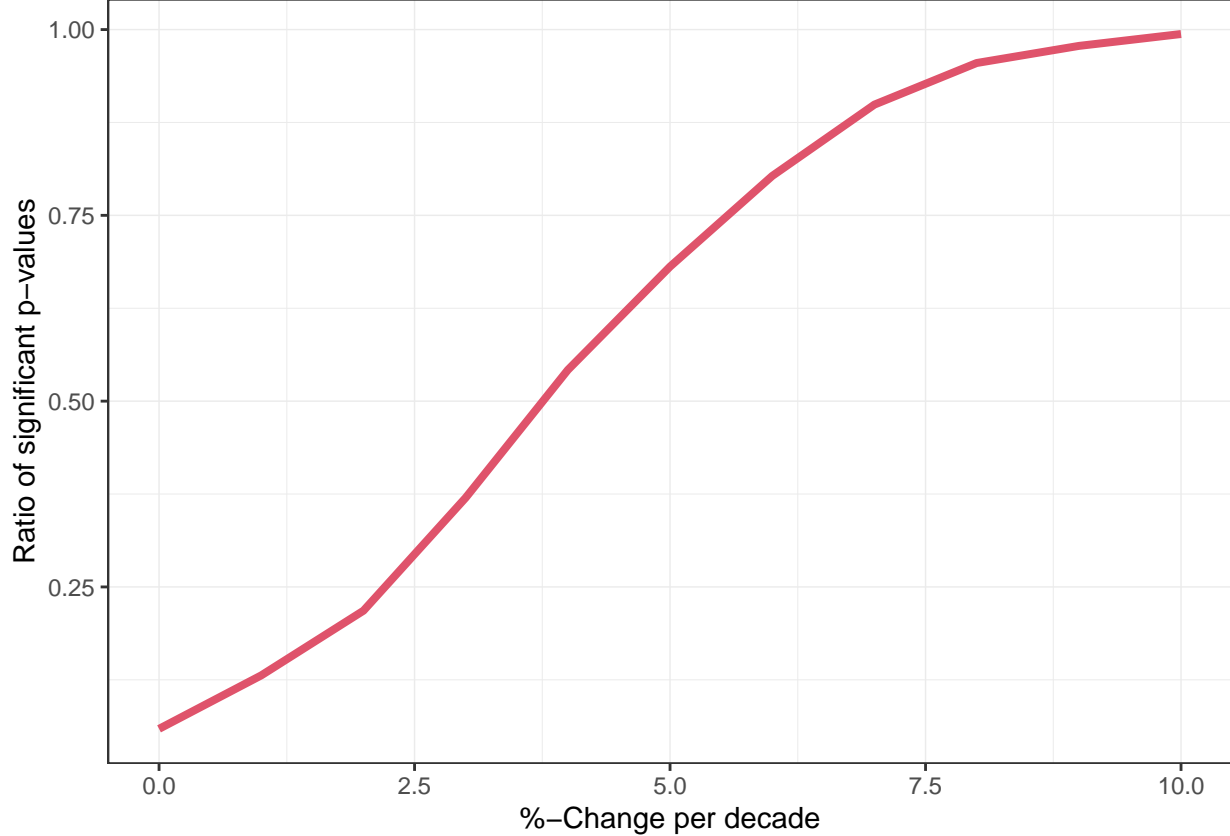
me series of annual maxima by a 21-year running window. The reference period is 1981–2010.

The time series also shows a clear minimum in the 1980s, whereas the anomalies increased since then. The signal of the smoothed time series visually shows a clear trend, but the noise of the raw time series covers the trend. Hence, the signal to noise ratio of our initial time series is too low that a trend can be detected in the time series. In a simulation study we can show, how high the trend would have to be, so it is likely to find a trend in the time series. To do so we first estimate the parameters of the GEV distribution of the raw time series with the lmomco package (Asquith (2024)).

```
##          xi          alpha          kappa
## 19.887010415  9.829072146 -0.009433245
```

For simplicity we assume a linear trend only in the location parameter, not in the shape or scale of the distribution. We add a monotonic trend of 1 % - 10 % for each decade. For a time series like ours, such an increase would almost double the location parameter for a 10 % increase. In case of a 1 % increase this would result in about 2 mm increase of precipitation for the location parameter for all 84 years. We replicate this simulation 1000-times and count the number of significant p-values (below 0.05) of a Mann-Kendall trend test of the resulting time series. To get an impression of the variability of the location parameter of the time series we estimate the location parameter with a 30-year running window.

Assuming a linear trend from the first to the last year, we yield a 3.52 % change per decade.

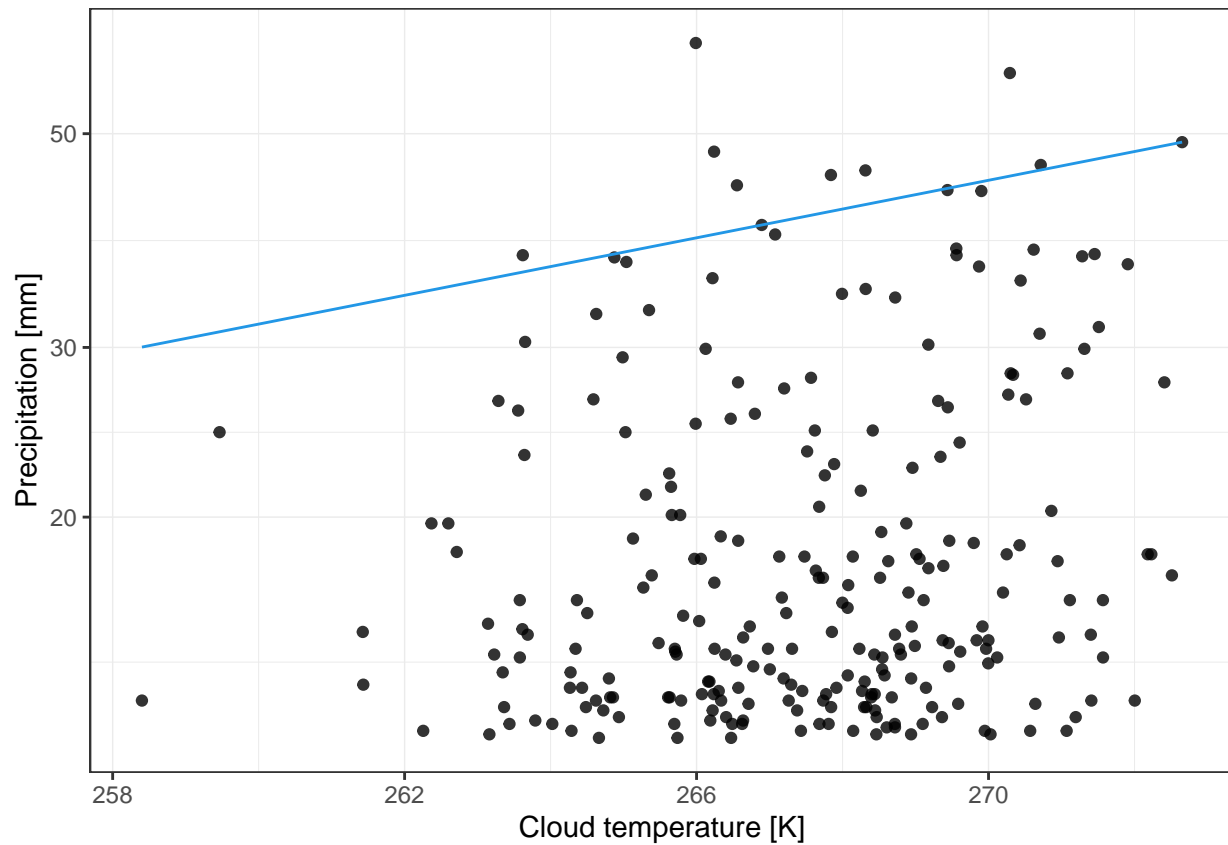


Our results show, that with a 10% monotonic increase per decade, the time series would output in most cases a significant test result. Considering the 3.52 % increase per decade, which can be somehow assumed for our time series - although it is likely not to be monotonic, the ratio of significant p-values is only 46.3 %. Although, there almost likely is a trend in our time series (visually inspected), the high variability in the annual maxima series would not yield a significant test result in about 50 % of the cases considering the assumed monotonic trend. This ratio should even be lower as the location parameter is decreasing from 1960 to 1980 for Vienna Hohe-Warte and increasing since then, generally showing no strictly monotonic behaviour.

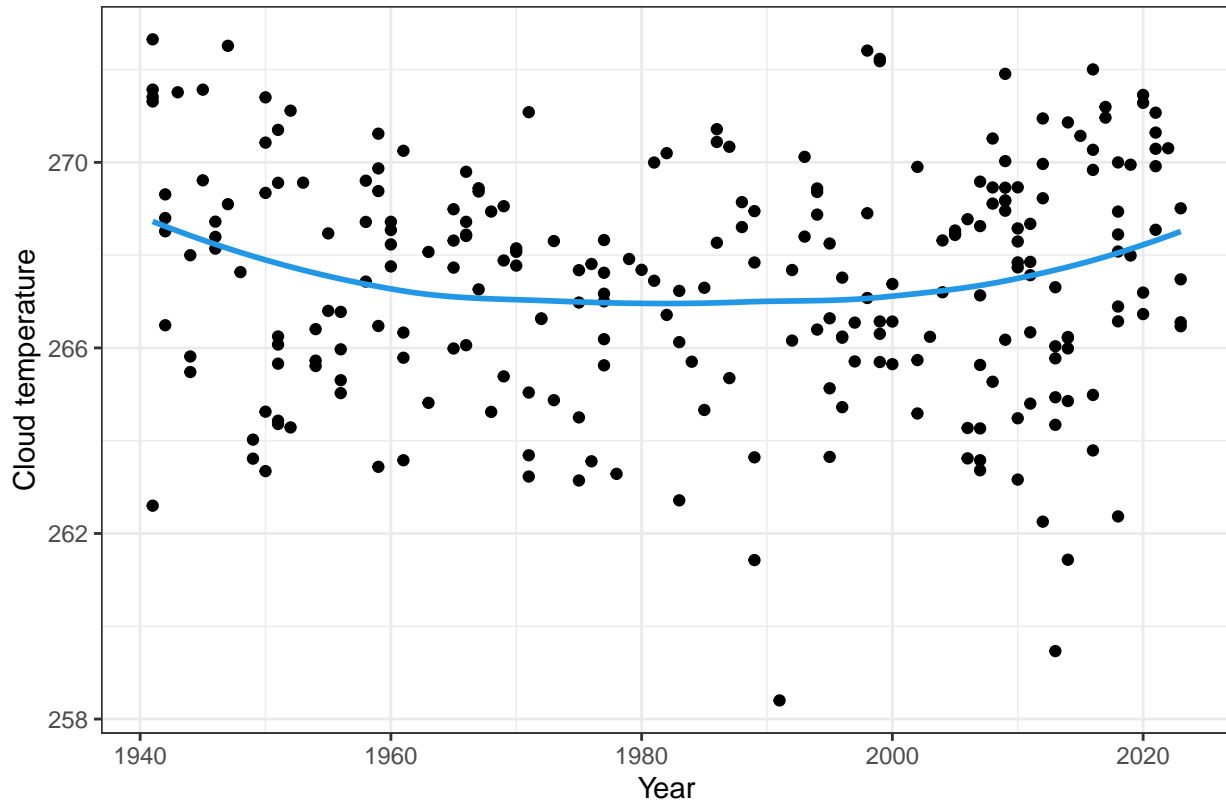
Trend considering CC-scaling

Some aspects of the inter-annual variability of the time series can be explained by large-scale phenomena. The minimum of the annual maxima time series in the 1980s can be related to the higher sulfide concentration, leading to increased cloud formation and less convective rainfall. Nevertheless, CC-scaling would tell us that extreme precipitation should increase with increasing temperature. Therefore, another possibility of identifying a trend would be to link the precipitation to a covariable which shows a clear temporal trend. In the case of extreme precipitation the best assumption is to relate extreme precipitation to temperature.

To increase the sample size for this next analysis (as it is also done in the revised manuscript), we use the $n * n_{year}$ maximum 2-hour precipitation events of the summer time series (only months May to September), where $n = 3$, and n_{year} is the number of available years. Each event is linked to the average cloud temperature (Average between the geopotential in 500hpa and 700 hpa), which was also used in a study for Vienna (Formayer and Fritz (2017)) and showed more reliable results in the high temperature extremes.

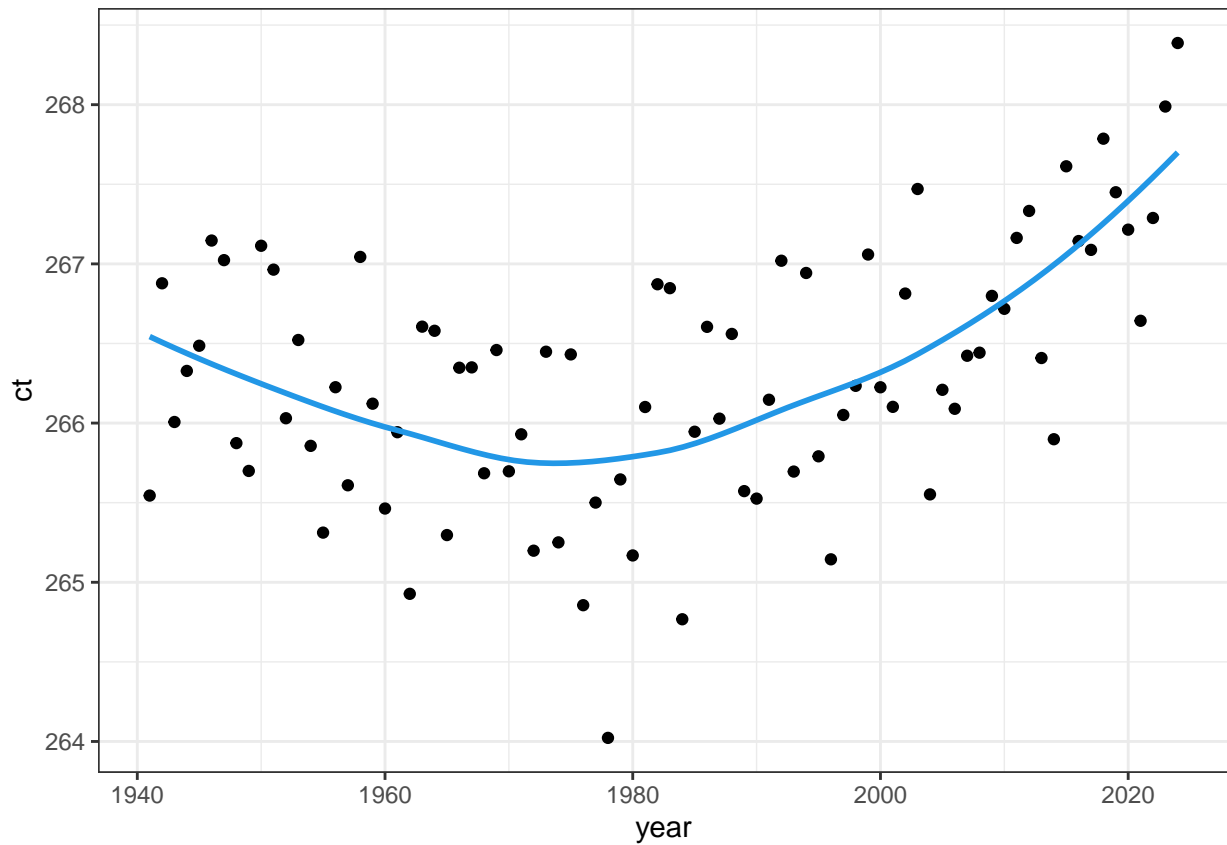


The plot shows the observed cloud temperature vs. the observed precipitation amounts. The line is a quantile regression of an approximately 10-year event. This clearly indicates, that increasing temperature will yield higher precipitation amounts. Considering now only the cloud temperature for these events plotted against the time, we can identify no real trend. We specifically see, that cloud temperature of the extreme events were very high in the 1940s and 1950s.



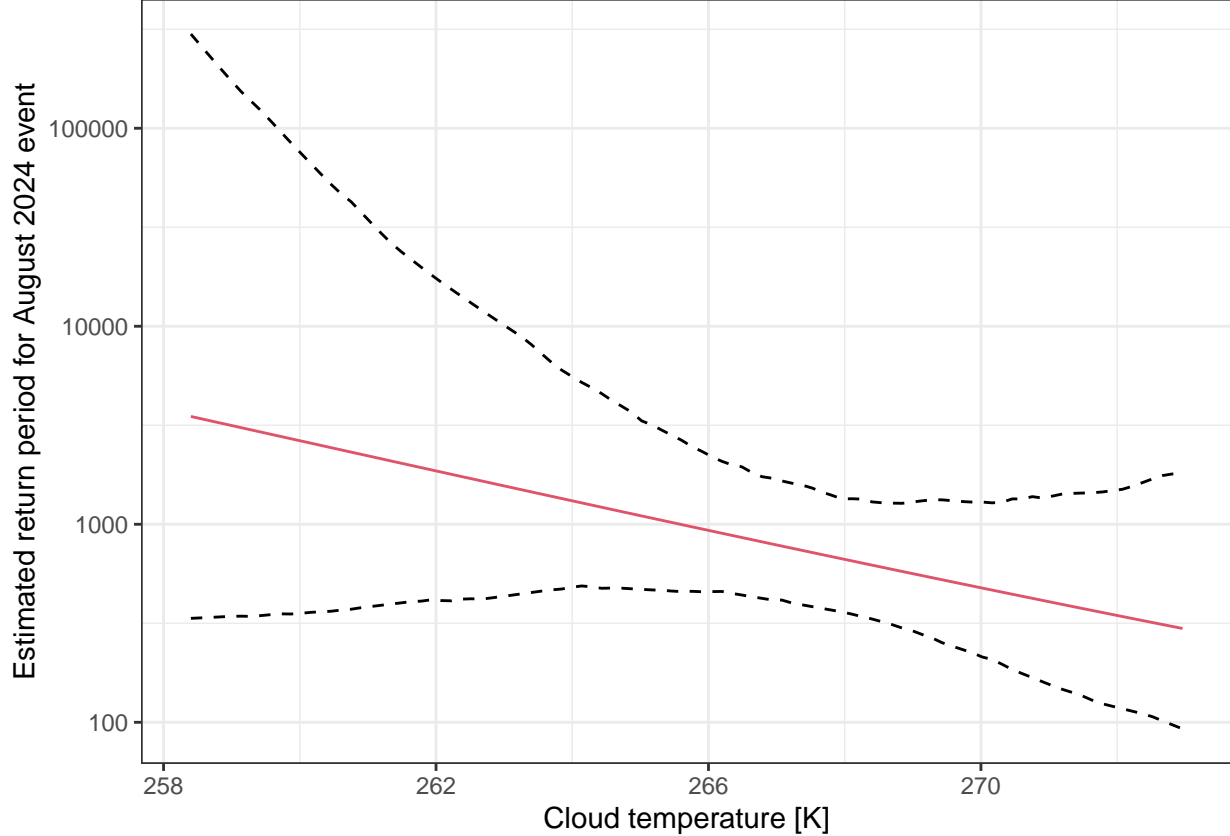
Cloud temperature of extreme summer 2-hour precipitation events at Vienna Hohe-Warte.

As an additional analysis step we can have a look at the average cloud temperature of the summer months for the time series from 1941-2024. The plot shows a decrease of cloud temperature from about 1 K between 1940 and 1970, and then a sharp increase since the 1980s. Accurate estimation of the cloud temperature should be highly dependent on radiosonde data, which was not available for the period before 1979. A possible bias in this data could lead to the high cloud temperature in these years, hence we can not link the trend in cloud temperature to the precipitation data.



Non-stationary model

Nevertheless, we see a strong increase in cloud temperature since the 1980s. Considering this trend, the likelihood of an extreme precipitation event such as the one in August 2024, without considering temperature as covariable may be too optimistic.



To have a similar approach to the Bayesian estimate of the final manuscript, we want to estimate the return period of such an event conditional to cloud temperature. Therefore, we are using a non-stationary bayesian estimate of a Generalized Pareto distribution. The computation is done inside the `bamlss` package in R (Umlauf et al. (2021)). We assume a possible linear effect for the scale and the shape parameter of the GP distribution. The return period for the observed cloud temperature of the August 2024 event would be 298 years on average, but with a credible interval from 93 years to 1818 years.

Conclusion

To summarize this short comment, our time series shows no trend as the variability of the underlying time series is covering the probable trend signal. Our simulation showed, that even an existing monotonic trend, will not be detected in most cases, unless it is larger than about 8 % per decade. Linking the extreme precipitation data to cloud temperature reveals a possible bias in ERA5 data of cloud temperature since the 1960s. Analyzing a non-stationary model for the 2-hour extreme precipitation to cloud temperature, leads to a decreasing trend in the shape and the scale parameter of the GP distribution. Finally, this results in a conditional return period of the event of approximately 298 years.

References

- Asquith, William H. 2024. *Lmomco—l-Moments, Censored l-Moments, Trimmed l-Moments, l-Comoments, and Many Distributions*.
- Formayer, Herbert, and Alexandra Fritz. 2017. “Temperature Dependency of Hourly Precipitation Intensities—Surface Versus Cloud Layer Temperature.” *International Journal of Climatology* 37 (1): 1–10.
- Haslinger, Klaus, Korbinian Breinl, Lovrenc Pavlin, Georg Pistotnik, Miriam Bertola, Marc Olefs, Marion Greiling, Wolfgang Schöner, and Günter Blöschl. 2025. “Increasing Hourly Heavy Rainfall in Austria Reflected in Flood Changes.” *Nature* 639 (8055): 667–72.
- Hersbach, Hans, Bill Bell, Paul Berrisford, Shoji Hirahara, András Horányi, Joaquín Muñoz-Sabater, Julien Nicolas, et al. 2020. “The ERA5 Global Reanalysis.” *Quarterly Journal of the Royal Meteorological*

- Society* 146 (730): 1999–2049. <https://doi.org/https://doi.org/10.1002/qj.3803>.
- Klaus, V., J. Laimighofer, and F. Lehner. 2025. “Brief Communication: How Extreme Was the Thunderstorm Rain in Vienna on 17 August 2024? A Temporal and Spatial Analysis.” *Natural Hazards and Earth System Sciences Discussions* 2025: 1–10. <https://doi.org/10.5194/nhess-2024-224>.
- Lehner, Fabian, Johannes Laimighofer, and Vinzent Klaus. 2024. “How Extreme Was the Thunderstorm Rain in Vienna on 17 August 2024? INCA Data and Station Data.” Zenodo. <https://doi.org/10.5281/zenodo.14500708>.
- Umlauf, Nikolaus, Nadja Klein, Thorsten Simon, and Achim Zeileis. 2021. “bamlss: A Lego Toolbox for Flexible Bayesian Regression (and Beyond).” *Journal of Statistical Software* 100 (4): 1–53. <https://doi.org/10.18637/jss.v100.i04>.